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QUANTITATIVE RESEARCH

Socio Economic Determinants of Customer’s Default Risk Assessing the Islamic Consumer Portfolio's Credit Factors in the Public Sector Bank: A Case Study

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Keywords

Islamic banking, Credit risk, Consumer Portfolio, Default Risk, Socio-economic factors, Shariah-Compliant financing.

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Abstract

Purpose: This study investigates the effects of borrower-specific characteristics such as education, occupation, employment duration, and socioeconomic status on default risk in a public sector bank in Pakistan. The study also assesses the effectiveness of the Consumer Risk Rating (CRR) system in predicting customer defaults.

Design/Methodology/Approach: The research is quantitative in nature and is applied to a case study of 100 cases drawn from 2,076 consumer financing accounts in a public-sector bank. Descriptive statistics, correlation analysis, linear regression, and probit models were used for data analysis.

Findings: The study found that borrower education, occupation, and job tenure significantly influenced CRR ratings and default risk. However, other factors such as gender, marital status, and income did not significantly affect the default probability. The CRR system appeared to be a useful predictor of customer default; higher scores corresponded to lower risk.

Originality: This research contributes to the literature on Islamic banking by incorporating socio-economic characteristics in credit risk models, which has not been considered by previous studies. The results of this study provide empirical evidence from an Islamic banking perspective, which provides practical insights for enhancing risk management in consumer finance.

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Implications: These findings suggest that Islamic banks need to improve their credit risk model by including socioeconomic factors for their borrowers to improve credit risk management and predict borrower default more accurately. This study offers practical implications for Islamic bank regulators and managers to enhance their risk assessment processes.

KAUJIE Classification: L25, L31, H11, H21, J32
JEL Classification: G21, G32, C31, C25, D14

INTRODUCTION

Islamic banking originated in the 1960s, when Dr. Ahmad El Naggar established an Egyptian bank, the Mit Ghamr Savings Bank, in 1963 (El-Gamal, 2006). The bank operated on a profit-sharing basis until 1967 without charging interest (Ahmed, 2002; El-Gamal, 2006). The Islamic Development Bank in Jeddah and Dubai Islamic Bank were founded to advance Islamic finance and banking in 1975 (El-Gamal, 2006). In evolutionary development, the two-tier Mudarabah model was established, allowing Islamic financial institutions to perform leasing to gain profit while also giving partners a share (El-Gamal, 2006). Following developments in Islamic finance, Takaful was introduced in 1979 as a Shariah-compliant alternative to conventional insurance and as an important component of the Islamic financial system (Billah, 2019). Asset-backed financing is an important feature of Islamic finance, whereas conventional finance generally relies more on interest-based lending and tradable financial claims, which Islamic finance restricts when they involve Riba or excessive uncertainty (El-Gamal, 2006). Usmani (2002) highlights Quranic verses that explicitly condemn Riba, such as Surah Al-Baqarah (2:275-279), which equates participating in Riba with declaring war on Allah and His Messenger.

Economic growth depends on a stable banking sector (Halling & Hayden, 2006). Statistical credit-scoring models estimate the likelihood of default or bankruptcy and support lending decisions (Sabato, 2010). These tools have evolved from univariate methods to multiple discriminant analysis (MDA), logit, probit, and neural networks (Altman, 1968; Hand & Henley, 1997). Financial services provided by banks include various services (Howells & Bain, 2008), and for these services, credit evaluation is necessary. Islamic banks incorporate borrower-specific and product-specific factors to lessen consumer risk

(Ahmed, 2011; Iqbal & Mirakhor, 2011). Islamic banks continue to evaluate their debtors to improve their risk procedures (Altman & Saunders, 1997; Saunders & Allen, 2002). In banking, risk assessment refers to estimating potential loss under uncertainty and ensuring controls that protect capital (Raghavan, 2015). Islamic finance risk involves uncertainty in contractual choices and is managed through Shariah-compliant instruments such as Murabaha, Ijarah, and Musharakah (Iqbal & Mirakhor, 2011).

Moreover, credit risk can be defined as the risk of loss resulting from non-fulfillment by a counterparty (Jorion, 2009). Islamic banks handle this risk through receivables and leasing (e.g., Murabaha, Diminishing Musharakah, or Ijarah) and through project-based products such as Salam or Istisna (SBP, 2008; Warninda et al., 2019). Despite the development of credit risk modeling, from simple statistical models (such as logit and probit) to sophisticated machine learning algorithms, there is a noticeable absence of context-sensitive research on Islamic financing portfolios, especially in emerging markets such as Pakistan. The bulk of prior research focuses on conventional banking systems and neglects the unique banking structure, ethical considerations, and business practices of Islamic banking, which may include Islamic modes of financing (e.g., Murabaha, Ijarah, and Diminishing Musharakah). Furthermore, existing studies have largely focused on financial, macroeconomic, or bank-specific factors rather than borrower-level socioeconomic factors and their impact on default risk in Islamic banking systems (Louzis et al., 2012; Shaheen et al., 2024). Similarly, sukuk assets are subject to value fluctuations in Islamic banking. Liquidity risk arises when Islamic banks fail to provide for obligations that are maturing, partly because of the limited depth of Shariah-compliant liquidity instruments in the market (Ahmed, 2011). Furthermore, while regulatory authorities such as the State Bank of Pakistan (SBP) have laid down guidelines for credit risk rating systems, there is limited empirical evidence on how robust these systems are in capturing socioeconomic factors in predicting default risk at the individual level. This study therefore examines whether borrower-level socioeconomic variables improve the assessment of default risk in an Islamic consumer portfolio; this is the study's own claim and is not attributed to prior authors.

Therefore, to achieve the objectives of this research study, a quantitative methodology was used. In quantitative research, statistical procedures are used to test an objective theory by examining relationships between variables (Creswell, 2003; Gunderson & Aliaga, 2003). A random sample of 100 cases was drawn from 2,076 Islamic consumer-financing records of the selected public sector bank. Equal selection probability was obtained using a simple random sampling strategy. Additionally, regression analysis was employed on the 100 sampled cases to check the relationship between the study’s variables, and as such, the determinants of credit risk could be validated within the consumer portfolio of the bank.

Furthermore, this study examines socioeconomic factors predictive of default risk in Islamic consumer financing at Public Sector Bank. using regression and probit models with a sample of 100 cases covering 2019 to 2023 to improve credit risk assessment. An effective risk rating system combines both operational configurations and software applications to forecast default probability. Through the diagnosis of socio-economic factors, this study aims to improve credit assessment and minimize the risks of default in Islamic banking.

The remainder of the paper is as follows: in Section 2, related literature is presented. Section 3 outlines the methodology of the study, and section 4 presents the hypothesis testing and results along with a discussion. Finally, the paper concludes with a conclusion.

LITERATURE REVIEW

Contemporary financial theory posits the idea that markets should operate with rationality. The CAPM is the earliest model capturing market rationality. The concept of Price Synchronicity Theory has evolved over time, with its origins dating back to Roll's work in 1988 (Roll, 1988). Roll observed that the degree to which stock movements align with market indices hinges on the impounding of market-level information and firm-specific in stock prices. Hence, SPS serves as a metric to capture company-specific information. This metric encompasses the market index, and its application is rooted in the understanding that company returns are influenced by a range of non-diversifiable factors and distinct corporate attributes.

Credit Quality and Credit Risk Modelling

Statistical credit-scoring models provide a quantitative measure of the likelihood that borrowers will exhibit a specific credit event, such as loan default, delinquency, or bankruptcy, given their current or future credit position with a financier (Altman & Saunders, 1997). Credit risk assessment has evolved from conventional statistical models to sophisticated data-based methods. Traditional approaches such as discriminant analysis and logistic regression rely on financial and personal characteristics to predict credit risk. However, as retail banking has grown and large-scale customer data have become available, more advanced techniques have come into play (Sabato, 2010). Credit scores allow managers to make quick or automated decisions, especially when banks deal with large customer portfolios with small profit margins (i.e., in consumer financing products) (Hand & Henley, 1997). Recent research shows that credit scoring models are increasingly being developed using machine learning (ML) and artificial intelligence (AI) to enhance performance (Lessmann et al., 2015; Ahmed et al., 2024).

According to Thomas et al. (2002), the FICO (Fair Isaac Corporation) score developed from the use of logistic regression and discriminant analysis to ascertain credit quality. At the beginning of the twentieth century, payment history and business performance characterized borrowers in the opinion of banks and lenders. Similarly, early rating systems were manual and lacked access to scientific information (Anderson, 2007). In the Basel framework, internal rating systems became important because banks were required to evaluate borrower default risk, portfolio risk, and rating validation more systematically (Van Gestel & Baesens, 2010; Sabato, 2010). Furthermore, early assessments of credit risk can be traced to the early twentieth century, characterized by reliance on manual evaluation of payment histories and business performance, which lacked scientific rigor (Anderson, 2007).

Default Prediction and the Role of Socio-Economic Factors

Much research has been conducted on default prediction models that consider the characteristics of borrowers (Avery & Berger, 1991; Bellotti & Crook, 2009; Abdou & Pointon, 2011). Previous studies are mostly concerned with financial dimensions of borrower information; however, recent studies indicate the growing relevance of socioeconomic dimensions such as income stability, education, and type of job, as well as other demographic factors. The reviews of default prediction models show that adding behavioral and socioeconomic variables to the models improves their performance and accuracy of risk classification. Moreover, empirical research using deep learning and data mining methodologies demonstrations that borrower features can show a major role in improving the accuracy of default prediction. Though, the literature also shows a disorganized approach to the use of these variables. In some researches, highlights on refined algorithms but does not make full use of socio-economic awareness within banking context. This outcome in a gap between the complication of the models and their practical applications particularly in the retail credit.

Credit Risk in Islamic Banking

Islamic banking brings distinct features that set it apart from the conventional banking system, mainly because of the prohibition of interest (Riba) and reliance on asset-based and risk-sharing-based financing (El-Gamal, 2006; Iqbal & Mirakhor, 2011). These characteristics affect credit risk. Prior studies suggest that Islamic banks' credit risk emanates from financing structures such as Murabaha, Ijarah, and Musharakah, in which the obligation to repay is linked to underlying economic transactions as opposed to interest-based financial contracts (Ahmed, 2011; Warninda et al., 2019). Empirical studies, however, concerning Islamic banking risk management are still limited when compared to the conventional banking. Recent studies in Pakistan have found that borrower-level factors have been largely overlooked in the studies of credit risk in Islamic banks, while the macroeconomic and bank-specific factors (including GDP, inflation, bank capital adequacy) were the main focus (Shaheen et al., 2024). Comparative research also indicates that although risk factors may be similar to conventional banking, the magnitude and implications of these factors differ because of Shariah-compliant banking structures. This suggests that Islamic banking studies have yet to effectively include socio-economic micro variables in their credit risk models, particularly for consumer portfolios.

Conventional and Contemporary Methods of Credit Risk Rating

The Altman Z-score is a significant credit risk assessment model developed in 1968, and the Merton model added the idea of a structural approach to the assessment of the default risk in 1974. Probability of default estimates were completed using an attempt to integrate financial ratio data with probabilistic methods. Machine learning (ML) emerged from major developments in data availability and computational capacity in the late twentieth century. Hand and Henley (1997) reviewed ML and statistical classification approaches, such as decision trees, neural networks, and support vector machines, which can identify relationships in unseen data. The transformation of credit assessment has accelerated with the availability of big data and alternative data sources.

Since 2021, artificial intelligence (AI) has increasingly been used in credit risk assessment, particularly for automated scoring, alternative-data analysis, and model monitoring. However, the literature does not suggest that AI has "complete control" over credit-risk assessment. Rather, current research emphasizes explainable artificial intelligence (XAI), model governance, and hybrid modeling as emerging directions (Lessmann et al., 2015; Arrieta et al., 2020). XAI methods offer solutions to regulatory and ethical requirements because they can provide transparent explanations of AI models.

Research Gap and Contribution

Credit risk modeling has attracted considerable attention in conventional banking; however, there is a gap in empirical research specifically related to Islamic consumer financing portfolios, particularly in developing countries such as Pakistan. The majority of studies focus on financial ratios (e.g., the Altman Z-score) (Altman, 1968), institutional and bank-specific risks (Louzis et al., 2012; Shaheen et al., 2024), or sophisticated modeling approaches, while relatively overlooking the impact of socio-economic factors of the borrower on credit risk. Additionally, the relevance and effectiveness of these models in Shariah-compatible financing models have not been well explored. Another key research gap is the lack of verification of regulatory credit risk rating models, such as those recommended by the State Bank of Pakistan (SBP). Although these standards specify rating systems, there is a shortage of empirical research that tests their effectiveness in capturing the actual factors that affect default risk. This study fills this gap by empirically testing borrower-level socioeconomic factors within an Islamic consumer portfolio and by assessing the Consumer Risk Rating (CRR) system against default outcomes. It also provides suggestions for enhancing risk rating systems, which will, in turn, support risk decision-making by bank managers, regulators, and policymakers.

State Bank of Pakistan BSD Circular 01 of 2013 and Guidelines

The guidelines issued by the State Bank of Pakistan (SBP) provide the regulatory basis for internal credit risk rating systems. BSD Circular No. 08 of 2007 required banks/DFIs to assign internal risk ratings across credit activities, including consumer portfolios, and specified a two-tier rating system (SBP, 2007). BSD Circular No. 01 of 2013 and BPRD Circular Letter No. 47 of 2020 further emphasized the development and implementation of internal credit risk rating models/scorecards to measure credit risk (SBP, 2013; SBP, 2020).

Rating Structure and Dimension:

The bank uses a one-dimensional rating on its consumer portfolio during the approval process known as obligor risk rating, in accordance with the approval of the State Bank of Pakistan (SBP).

The Rating Process & Review

Consumer risk ratings, as per SBP's guidelines, shall also be assigned and approved, together with the credit granting process. The rating of the borrower of the concerned branch is responsible for the borrower rating, and prepares the proposal. Furthermore, the guidelines indicate that the loan sanctioning authority approving the loan shall also verify or recalculate the rating given by the branch at every stage of the approval process.

System implementation

Any rating system can be successful only if it is implemented in both letter and spirit. Although responsibility for monitoring the use of the scoring system should be vested in the risk department, responsibility for implementing the scoring system should lie with the credit officer and various levels of the approving authorities.

Data maintenance

The ratings information should be treated as internal bank data, and even when the relationship with the borrower ends, it will remain stored. The task of maintaining and storing data securely belongs to the risk department and the branch/concerned approving authority.

Rating system validation, modification, and approval

Risk rating models may fail to perform as desired, in such cases, validation is performed to determine the level of alignment between the model's output and its actual performance. The assessment is compared to the extent to which the model assigns a better score to good loans than bad loans and minimizes the areas of type I (actually rejected) and type II (actually accepted) errors. A type II error occurs when the bank enforces a 60 percent minimum score in qualifying a customer as low-risk, but it also results in the rating system being regularly reviewed and updated by the risk department.

Rating Reporting in e-CIB

The affected branches will also provide rating grade mapping along with the State Bank of Pakistan rating grade in the monthly e-CIB report.

Types of Consumer Risk Rating Model:

In Shariah-based Islamic banking, consumer risk rating models are commonly linked with product-specific financing structures, including salary or personal financing based on Murabaha, auto finance based on Ijarah, and house finance based on Diminishing Musharakah. Personal loans (Murabaha) refer to loans to individuals to pay for goods, services, and expenses and cover the revolving credit running finance to individuals. Housing finance involves giving loans to a person to buy an apartment/residence, house, etc. Housing finance is a low-risk product among all other consumer products because of the nature of the underlying security (house). Moreover, auto finance, under the Ijarah financing model, is defined as loans that are taken to purchase an auto for personal use. Nearly all banks in Pakistan now finance automobiles (cars). The model used to evaluate auto loan borrowers considers both quantitative and qualitative factors. Risk rating grades help banks determine the level of risk associated with each customer and facility. The length of the risk grades negatively affects the accuracy of the ratings, leading to subjective, time-consuming decisions that pose an administrative problem. The reduction in the number of grades makes it difficult to distinguish between customer risk levels. The bank follows the 12-point consumer risk scale specified by the State Bank of Pakistan (SBP), which includes nine outstanding ratings and three default ratings. Any rating lower than 60 is not allowed, and a waiver or designation must be signed by the managing director/CEO.

Table 1: Obligor Risk Rating Scale

Obligor Risk Rating Scale						
Scale	Score Range	Description Risk Rating	Risk to the Bank	Salary Loan (Fix Rate%)	Auto Fin	House Fin
12	91 ~100	Superior	Minimal Risk	26	1 Yr K+2.0	1 Yr K+2%
11	81 ~ 90	Very Good	Very Low Risk	27	1 Yr K+2.5	1 Yr K+3%
10	71 ~ 80	Good	Low Risk	28	1 Yr K+3.0	1 Yr K+4%
9	61 ~ 70	Satisfactory	Moderate Risk	29	1 Yr K+3.5	1 Yr K+5%
8	56 ~ 60	Acceptable	Acceptable Risk	30	1 Yr K+4.0	1 Yr K+6%
* 7	51 ~ 55	Average	Average Risk	31	1 Yr K+4.5	1 Yr K+7%
* 6	46 ~ 50	Below Average	Below Average Risk			
* 5	41 ~ 45	Watch	Potential for default			
* 4	36 ~ 40	Borderline	Unacceptable Risk			
* 3	31~35	Sub-standard	Partial Loss			
* 2	26~30	Doubtful	Fully repayment Questionable			
*1	00~25	Loss	Loss			

Table 1 shows the Obligor Risk Rating Scale, where the credit risk of borrowers is ranked on a scale of 12 (highest rating, superior, lowest risk) to 1 (highest risk, loss). It highlights the risk levels and their effect on Islamic financing products, namely Salary Loans (Murabaha), Auto Finance (Ijarah), and House Finance (Diminishing Musharakah). Since borrowers with higher ratings such as 12 enjoy good financing rates at low rates, those with lower ratings such as 1 do not have access to better rates.

Characterizations of the factors (variables)

Gender

Social reputation and financial responsibility reduces the chances of female borrowers defaulting on their loans, as per conventional wisdom and experience.

Marital Status

Married couples are less likely to default in comparison to singles since they are more mature and sensitive to their status in society and responsibility to their families.

Dependents

Dependents refer to family members who rely financially on the borrower, such as children, spouse, parents, or other household members without independent income. There is a direct relationship between the number of dependents and the probability of default, because an increase in dependents may increase financial obligations and reduce repayment capacity.

Age of the customer

Age of the customer is relevant because Active spending decreases with age as people accept the responsibility of children and adopt more careful financial planning. Similarly, the risk of default decreases with the age of customers.

Education

Occupation of the customer

The scoring system favors permanent employees because contractual employment may involve greater uncertainty. Verifiable net income is the most important consideration for expenditure and the capacity to repay debt. The lower the income, the higher the probability of default, and vice versa.

Length of business/employment

The business or length of employment determines the level of expertise development in the person, which results in greater employment or business stability.

Residence landline number

Landline numbers provide a relatively stable contact point because cell phone numbers can change with ease.

Residence Type (Ownership Structure)

This factor reflects the social and financial stability of the individual, as applicants with owned premises are less likely to default or, conversely, more likely to repay. In the case of rented accommodation, there is both a relocation risk from a collection perspective and a cash outflow burden from a payment perspective.

Utility bills payment behavior

Utility bill payment behavior: The payment behavior of utility bills indicates financial discipline and responsibility of the customer and the residence verification address.

Source(s) of income

Individuals with multiple sources of income generally reflect stronger financial strength and stronger debt-repayment capacity as compared to individuals with a single source of income.

Depth of the Credit

Age of Credit (Relationship with the Bank)

In general, an existing customer should be perceived as being less risky than a new one simply because a relationship already exists and the bank would be able to predict, with a reasonably higher level of certainty, his/her behavior based on experience.

Number of Credit Accounts

The fewer the credit facilities used by the customer, the lighter the debt burden, and eventually the lower the chance of default.

Payment History ECIB Report

For a clear Electronic Credit Information Bureau (e-CIB) report, a score of 5 will be assigned; in case of a negative or unclear report, the score is reduced according to overdue payment history. Payment overdue status: no late payment in the history is awarded the highest score, i.e., 5, and the score is decreased with an increase in the number of days in the late payment history record.

Other Variables Tenure

Higher tenure of the exposure increases the uncertainty. This risk is reflected in the model through scoring. The highest score is assigned to the shortest tenure.

Debt to burden ratio

The debt-burden ratio is a direct measure of repayment capacity, and it uses one's monthly income in relation to one's monthly debt expenses. The lower ratio implies insignificant effects of new debt on the cash flow, increasing the repayment ability. It is stated as follows: Debt burden ratio = (Total installment amount ÷ Total net income)

Average monthly bank balance

It serves as a proxy for income and also reflects the stability of the cash flow. The higher the average balance, the higher the score. To this end, the average monthly bank balance is to be computed as follows: Average Monthly Bank Balance = (Balance at the last date of the month ÷ Total Number of months used).

RESEARCH METHOD

Conceptual Framework

This study proposes a combined conceptual framework to know a customer's default risk in Islamic consumer financing, information asymmetry theory, behavioral finance and illustration on credit risk theory. Credit risk theory suggests that default occurs when a borrower's repayment capacity is unsatisfactory to meet financial promises; however, in retail portfolios, repayment capacity is taken not only by financial indicators but also by socio-economic factors that reflect stability and creditworthiness.

Information asymmetry theory suggests that lenders have imperfect information about borrower behavior and therefore use information such as income, occupation, education, and demographic characteristics to assess loan applications. Behavioral finance adds that personal finance decisions are based on life-cycle effects, financial awareness, and social obligations, which contribute to repayment capacity and behavior. Hence, the chosen socio-economic factors are justified and interrelated rather than independent. Age, employment tenure, occupation, and income reflect repayment capacity and stability; education reflects financial literacy and decision-making; age reflects life-cycle effects on risk and financial planning; marital status and dependents reflect financial responsibility and expenditure; residence ownership, banking habits, and utility payment habits reflect financial stability, financial discipline, and reliability. These factors are incorporated into the three analytical factors: repayment capacity, financial behavior, and socio-demographic stability, which in turn affect both the Consumer Risk Rating (CRR) and default probability. This holistic approach offers a coherent foundation for the empirical models developed in this study and enhances the conceptual link between borrower attributes and credit risk in the context of Islamic banking.

Research Design

The research design of this study is based on the quantitative approach. According to Gunderson and Aliaga (2003), the quantitative research approach improves the collection of numerical data and subsequent statistical procedures. Similarly, Creswell (2003) argued that quantitative research uses objective theories and tests the relationships between variables. Under the quantitative research approach, this study employed regression models, including linear and probit regression. It provides less bias compared to mixed approaches, improves forecasting, and enables the capacity to work with larger datasets. Statistical software tools such as EViews and Excel improve on the risk rating model applicable to Islamic banking operations. Hence, these models have been used in the study's analysis.

Population and sample of the study

The population of the study consists of 2,076 Islamic consumer-financing cases from Public Sector Bank, from which a simple random sample of 100 observations was drawn for the econometric analysis. This was done to ensure data quality, uniformity, and consistency of variables, as not all observations in the full population had the complete information required for regression and probit analysis. The sample comprises only those cases that have complete and validated socio-economic and credit-related information, enhancing the validity of the empirical study.

Simple random sampling was used to ensure an equal chance of each observation in the population being selected, thereby reducing selection bias and improving representation. Moreover, the sample was carefully designed to include observations with varying Consumer Risk Ratings (CRR) to account for differences in the risk level of borrowers. Because this is an exploratory case study based on one bank, the sample size is treated as adequate for preliminary model validation rather than for industry-wide generalization (Abdou et al., 2007; Sabato, 2010). Moreover, with a relatively low default rate (around 8%) in the data, the study ensures that the number of defaults is adequately represented in the sample to retain meaningful information for the probit model. This is critical since defaults are often rare events in consumer portfolios and it is important to adequately sample to ensure sufficient variation in the response variable.

A larger sample would be desirable for enhancing representativeness, but the chosen sample size is considered adequate to detect statistically significant links between socio-economic factors and default risk, particularly for an exploratory case study. This is a limitation of the study, and it is suggested for future research to include larger samples from multiple institutions for greater robustness and generalizability. The following are the frequency tables for each variable:

Table 2: Variable Coding and Measurement

Variable	Role in analysis	Measurement/Coding	Purpose
CS (Classification Status)	Dependent variable in probit model	1 = Default; 0 = Non-default	Indicates observed default outcome
CRR (Consumer Risk Rating)	Dependent variable in OLS; predictor in probit	12-point scale; higher score = better credit quality	Measures borrower credit quality
Gender	Independent variable	1 = Male; 0 = Female	Demographic factor
Marital Status	Independent variable	1 = Married; 0 = Unmarried	Household stability indicator
Dependents	Independent variable	Number of financially dependent family members	Financial burden indicator
Age	Independent variable	Age in years	Life-cycle and maturity indicator
Education	Independent variable	1 = Primary; 2 = Middle; 3 = Matric; 4 = Intermediate; 5 = Graduate/Master	Human capital/ financial awareness indicator
Occupation	Independent variable	1 = Business; 0 = Salaried	Employment category indicator
Net Income	Independent variable	Monthly net income in million PKR	Repayment-capacity indicator
Length of Job/ Business	Independent variable	Number of years in current job/business	Income stability indicator
Landline	Independent variable	1 = Yes; 0 = No	Residence/contact stability proxy

To reduce Type I and Type II decision errors, this study compares the Consumer Risk Rating (CRR) results with the observed default classification and uses both OLS and probit outputs to check whether accepted and rejected risk signals are consistent with actual borrower performance.

Hypothesis

Null Hypothesis H_0

Credit Risk Rating and Default (status) are unrelated to (and hence not positively and negatively associated with) Gender, Marital Status, Number of Dependents, Age, Education, Occupation, Net Income, Length of Job, and Presence of Landline Number.

Alternative Hypothesis H_a

Gender, marital status, number of dependents, age, education, and occupation have significant relationships (either positive or negative) with credit risk rating and default (classification status), net income, length of employment, and presence of a landline number.

Research Question

This study is guided by the following research questions: How significant are the socio-economic variables in determining the default risk of Islamic consumer finance customers, and how well does the current credit risk rating system capture such default risk?The study addresses possible Type I and Type II errors by validating the direction and significance of borrower characteristics across the CRR model and the default-probability model rather than relying on one statistical test only.

Consumer Risk Rating (CRR) Scale and Dependent Variables

This study adopts a 12-point ordinal Consumer Risk Rating (CRR) scale, with higher ratings indicating superior credit quality and low default risk, and lower ratings indicating inferior credit quality and high default risk (or loss). In particular, a score of 12 is “Superior” (best credit quality/least risk), while a score of 1 is "Loss" (worst credit quality/maximum risk/default). Therefore, this scale is positively ordered in terms of creditworthiness. CRR is considered a measure of credit quality. As a result, in the regression methodology, a positive coefficient suggests an increase in credit quality (i.e., a decrease in risk of default) and a negative coefficient suggests a decrease in credit quality (i.e., an increase in risk of default). This is essential for the proper interpretation of the socio-economic variables and borrower risk. Besides the CRR, the study also uses a binary variable for default in the probit model (Default = 1) as the dependent variable, where 1 denotes the borrower has defaulted and 0 denotes a non-default (performing loan). Here, a positive coefficient raises the probability of default, and a negative coefficient lowers the probability of default.

Research Models

The study uses two complementary models: the linear regression model estimates the drivers of Consumer Risk Rating (CRR), whereas the probit model assesses the probability of default as a binary outcome. This dual-model approach is used because CRR measures credit quality on an ordinal rating scale, while default is a yes/no outcome. Therefore, conclusions are drawn from both models: OLS explains variation in the bank's risk rating, while probit validates whether CRR and borrower characteristics predict actual default. The validity of assumptions, such as linearity, independence of errors, multicollinearity, and normality of residuals, has been considered, and diagnostic tests (correlation matrix and goodness-of-fit) have been employed to validate the findings. Special care is taken in interpreting the coefficients: in the regression model, positive coefficients signify improved credit quality (higher CRR and lower risk), while negative coefficients signify reduced credit quality; in the probit model, coefficients represent the direction of change in default probability, with marginal effects being used to provide economically meaningful interpretation of the magnitude of the effects.

The variables were chosen on the basis of their theoretical significance as indicators of cash-flow ability, financial habits, and borrower stability.

Linear Regression Model:

$CRR_i = \alpha + \beta_1 Gender_i + \beta_2 Marital\ Status_i + \beta_3 Dependents_i + \beta_4 Age_i + \beta_5 Education_i + \beta_6 Occupation_i + \beta_7 Net\ Income_i + \beta_8 Length\ of\ Job/Business_i + \beta_9 Landline\ Status_i + \varepsilon_i$ … Eq. (1)

The Probit Regression Model:

$Default_i$ (Classification Status) = f($CRR_i + \beta_1 Gender_i + \beta_2 Marital\ Status_i + \beta_3 Dependents_i + \beta_4 Age_i + \beta_5 Education_i + \beta_6 Occupation_i + \beta_7 Net\ Income_i + \beta_8 Length\ of\ Job/Business_i + \beta_9 Landline\ Status_i + \varepsilon_i$) … Eq. (2)

DISCUSSION

Analysis of Data

In this section, Consumer Risk Rating (CRR) is treated as the dependent variable in the OLS model, while Classification Status (CS/default) is treated as the dependent variable in the probit model. The analysis uses the selected socio-economic variables to determine their reliability and economic rationale in relation to consumer risk rating and default behavior.

Descriptive statistics

In this section, the study's data have been reported. The following table shows the descriptive statistics, such as mean, standard error, median, mode, etc. Descriptive statistics constitute almost all the analysis of quantitative data, which in research can be numerous measures.

Table 3: Descriptive or Summary Statistics

Variable	Mean	SD	Median	Mode	Range	Min	Max
CS	0.08	0.273	0	0	1	0	1
CRR	9.81	0.72	10	10	3	8	11
Gender	0.95	0.219	1	1	1	0	1
Marital Status	0.98	0.141	1	1	1	0	1
Dependents	2.98	1.371	3	3	7	0	7
Age	41.91	9.026	41	50	39	23	62
Education	4.33	0.829	5	5	2	3	5
Occupation	0.12	0.327	0	0	1	0	1
Net Income (M)	0.091	0.185	0.045	0.047	1.183	0.014	1.196
Length of Job	14.37	8.282	12.5	10	32	2	34
Landline	0.1	0.302	0	0	1	0	1

Note: M = mean, SD = standard deviation, Mdn = median. CS = Classification Status (1 = default; 0 = non-default), CRR = Consumer Risk Rating. Net income is reported in million PKR.

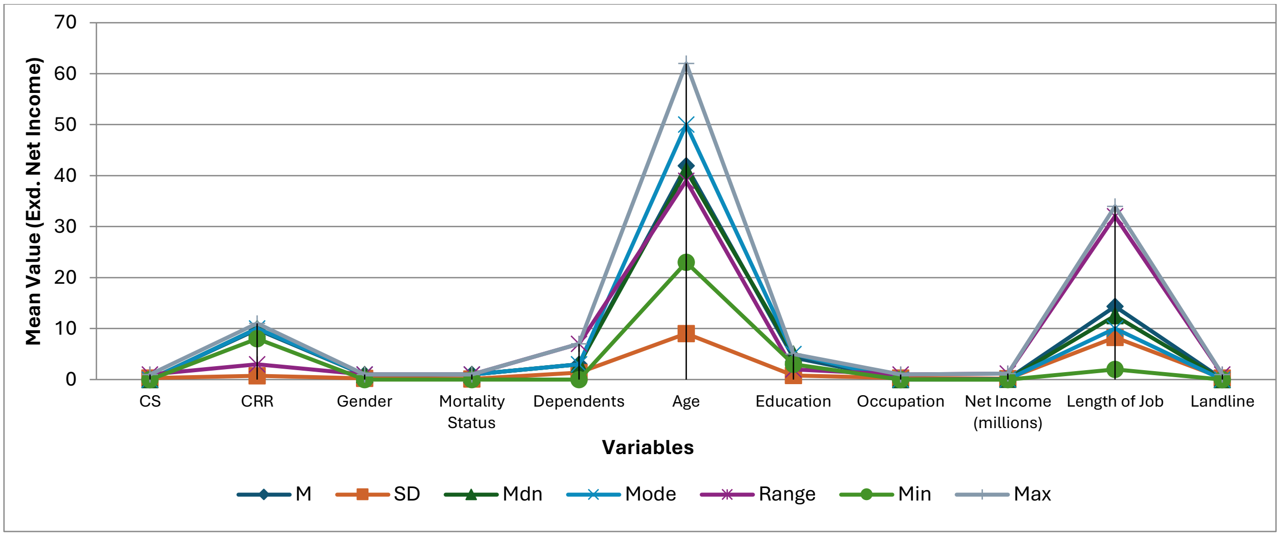

Figure 1 Descriptive Statistics of Mean Values of Variables

The key statistics of the variables in the data are shown in Figure 1: the distribution, median, and average. The distribution of net income is skewed, and this is the reason why it is highly variable. Age is approximately normally distributed; gender and marital status show low variation because most observations are male and married. The CS mean of 0.08 indicates an 8% default rate rather than a credit score average. This statistical analysis involves measuring the data of different variables in the study of 100 individuals.

Moreover, most people are given a CRR (Consumer Risk Rating) of 10, and the general average is 9.81, which demonstrates a stable distribution with little variance. Similarly, the gender mean of 0.95 indicates that the sample is predominantly male. Additionally, marital status denotes that 98 percent of these people are married (value = 1), whereby there is little difference in data points. Furthermore, the mean number of dependents is 2.98, with the majority having three. The distribution is close to the normal pattern, although it is slightly skewed. The participants were close to a mean age of 41.91 years, with a moderate deviation. The mean education level is 4.33, and the majority attain level 5. Occupation is coded as 1 for business and 0 for salaried; therefore, its low mean reflects the dominance of salaried customers. The mean net income is 0.0914 million PKR, and the median is 0.0452 million PKR, indicating significant differences because of outliers with high net incomes and considerable skewness.

In addition to this, the descriptive statistics in Table 3 show that the average amount of time that subjects have worked in their job position is 14.37 years, with a small skew in the distribution, with most of them having worked for ten years. Moreover, ownership of landlines has a mean of 0.1, but most people do not possess one (value = 0). Hence, the data are skewed. Similarly, in general, the data set has varied distribution patterns and dispersion levels. The largest outliers belong to net income, while gender and marital status have low variability. These descriptive patterns justify the use of regression and probit analysis because the variables differ in scale, dispersion, and distribution.

Correlation Matrix

The term "correlation" is commonly used because it describes the degree of linear association between different variables. Table 3 presents the essential variable statistics, which include distribution information, median, and average values. Net income demonstrates significant variability because of its highly skewed distribution. Age is normally distributed. The distributions of gender and marital status show uniformity throughout the sample since the study employs balanced methods.

Table 4: The Correlation Analysis

Variable	1	2	3	4	5	6	7	8	9	10	11
1. CS (Default)	—										
2. CRR	-0.28	—									
3. Gender	-0.13	0.15	—								
4. MaritalStatus	-0.22	0.06	-0.03	—							
5. Dependents	-0.08	0.06	0.13	0.31	—						
6. Age	0.05	0.15	0.13	0.22	0.41	—					
7. Education	-0.12	0.38	-0.19	-0.03	-0.09	-0.04	—				
8. Occupation	0.17	0.27	0.08	0.05	0.03	0.21	-0.11	—			
9. NetIncome	-0.05	0.26	0.03	0.05	0.15	0.32	-0.08	0.57	—		
10. LengthOfJob	-0.11	0.23	0.14	0.21	0.35	0.72	-0.04	-0.05	-0.04	—	
11. Landline	0.02	0.32	-0.23	0.05	0.15	0.03	0.23	0.08	0.23	0.06	—

Note. All correlations are Pearson's r, rounded to 2 decimals. CS = Classification Status/default indicator, CRR = Consumer Risk Rating.

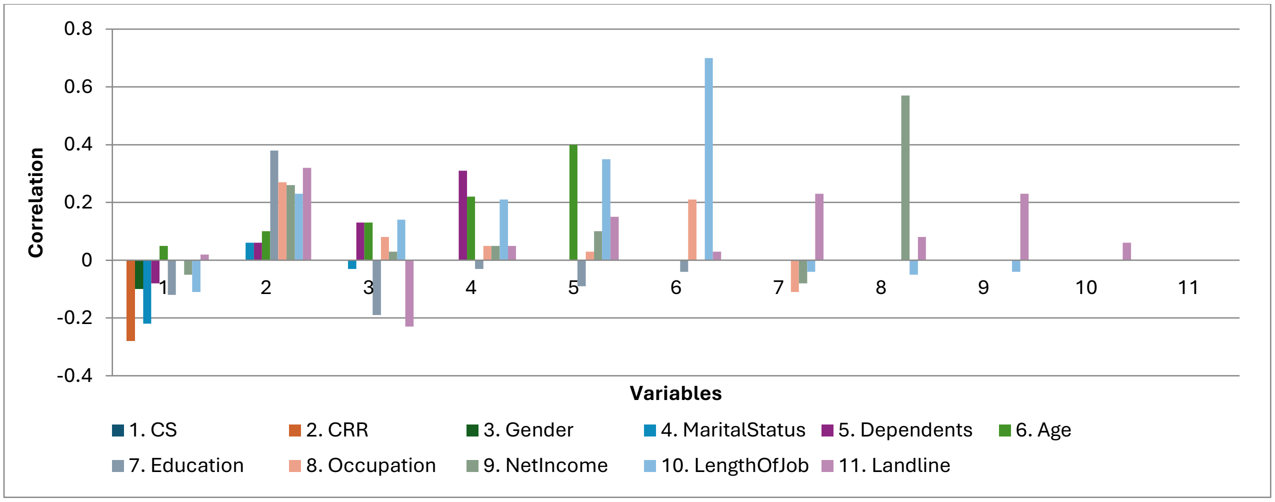

Figure 2: Correlation Coefficients with Consumer Risk Rating (CRR)

Moreover, in Table 4, the negative correlation between CS/default status and CRR (-0.28) indicates that defaulted cases are associated with lower consumer risk ratings. There is a weak negative relationship (-0.10) between gender and default status, which indicates only a slight difference in default status across gender. A positive correlation (0.38) indicates that a higher level of education correlates with higher credit risk ratings. Occupation also shows a positive relationship with CRR (0.27), and net income has a positive relationship with CRR (0.26), indicating that income and occupation may support better credit quality.

Furthermore, there is a positive relationship (0.40), which means older adults take care of more dependents. There is a positive correlation (0.35) between job length and the presence of dependents among the employees, implying that employees with longer careers are likely to have dependents. There is a significant positive relationship (0.65), which is an indication that older workers are less mobile. There is a negative, weak correlation (-0.11) in association with a higher level of education and the ability to open occupational variety. There is a highly positive relation (0.57), meaning that some jobs lead to a higher net income. There is a positive relationship with landline (0.23), depicting that the higher the earner, the more likely he/she is to have a landline. There is a positive correlation of 0.70 supports the fact that older people stay in their jobs longer. The positive value of correlation (0.23) shows that more educated people use landlines more frequently.

Landline phone ownership has a positive relationship with net income (0.23), which implies that the more people have a higher earning capacity, the more likely they are to maintain landline services (23). Correlation analysis shows that net income has highly significant relationships with five variables: age, job tenure, education, job, and credit ratings. These econometric and financial relationships are complex and require multivariate treatment. Therefore, there is a necessity for a detailed study. When we look at these connections, positive and negative connections have to be interpreted together.

Regression Analysis

Binary probit regression is used when the dependent variable has two possible outcomes, such as default and non-default. In this study, the dependent variable is Classification Status (CS), where 1 indicates default and 0 indicates non-default. The results imply that CRR is a major factor in default probability, married people have a lower default probability, and net income has no statistically significant effect. The model explains 30.2 percent of variation in default. In the analysis, the estimation of DEFAULT is based on 100 observations using the Newton-Raphson method, as reported in Table 5.

The intercept (9.377, p = 0.0523) for the regression is not statistically significant. AGE is weakly and insignificantly associated to loan default (coefficient = 0.0626, p = 0.1450). CRR has a significant effect on the default probability (coefficient = -1.017, p = 0.0494). Three dependents show a very weak, non-statistically significant relationship between them and default (coefficient = -0.0559, p = 0.7816). The attainment of higher education indicates that the probability of defaulting is low (coefficient = -0.0886, p = 0.7886), but it is not significant. The probability of default is lower in the case of male borrowers (coefficient = -1.0107, p = 0.2934), albeit insignificant. The ownership of landline phones has a minor increase in the probability of defaults (p = 0.3805), which is not significant. Default risk is negatively affected by job duration (coefficient = -0.0243, p = 0.5628), although the effect is not significant. Married subjects have a lower default chance (coefficient = -2.2044, p = 0.0814), though it is weak. The probability of default does not correlate with net income (coefficient = 7.22E-08, p = 0.9687). The influence is very weak and low (coefficient = 0.0701, p = 0.9428).

Table 5: The Probit Model Regression

Variable	Coefficient	SE	z	P
Intercept	9.377	4.831	1.94	0.052

Age	0.063	0.043	1.46	0.145
CRR	-1.017	0.518	-1.97	0.049
Dependents	-0.056	0.202	-0.28	0.782
Education	-0.089	0.303	-0.27	0.789
Gender	-1.011	0.962	-1.05	0.293
Landline	0.87	0.993	0.88	0.381
Length of Job	-0.024	0.042	-0.58	0.563
Marital Status	-2.204	1.265	-1.74	0.081
Net Income	0	0	0.04	0.969
Occupation	0.07	0.977	0.07	0.943

Note. N = 100. Dependent variable: Default/Classification Status (0 = non-default, 1 = default). CRR = Consumer Risk Rating. McFadden $R^2 = .302$. Log likelihood = –19.447.

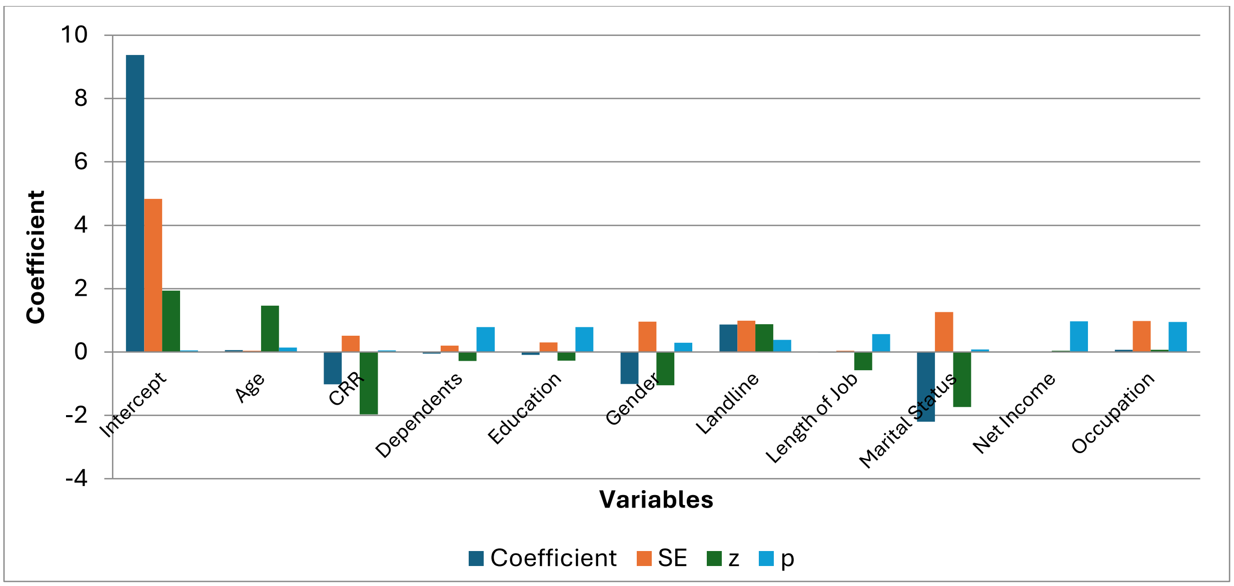

Figure 3: The Probit Model Coefficients for Default Prediction

The McFadden R-squared value shows that the model accounts for 30.2 percent of the variation in the default status. The likelihood ratio statistic with a value of 16.86 indicates that the model is marginally significant for predicting default status, with a p-value of 0.0775.

The average default rate of the overall sample is 8 percent, which can be converted to 0.08. Out of the total observations, there were 92 non-defaulted cases, whereas 8 of the observations were defaulted (Dep = 1). According to the binary probit analysis, CRR and marital status are the significant factors that influence default risk, and the married customers and the clients with higher credit scores have lower default risk. Net income, education, and age did not have meaningful associations with default. The model shows a good fit, and it explains about 30 percent of variation in default status.

The OLS regression model for CRR explains 38.7 percent of the variability in Consumer Risk Rating, and the multiple R equals 0.6222, which shows a moderate relationship between the observed and predicted CRR values. The R-squared value of 0.3871 demonstrates that 38.71% of variability in CRR is explained by the independent variables. The adjusted R-squared of 0.3258 accounts for model complexity and sample size. The standard error value of 0.5916 means that the observed CRR values differ from the predicted CRR values by an average of about 0.5916.

Table 6: Regression Statistics for the OLS Model

Statistic	Value
Multiple R	0.622
R^2	0.387
Adjusted R^2	0.326
Standard Error	0.592
Observations	100

Note: **DV:** Consumer Risk Rating (CRR)

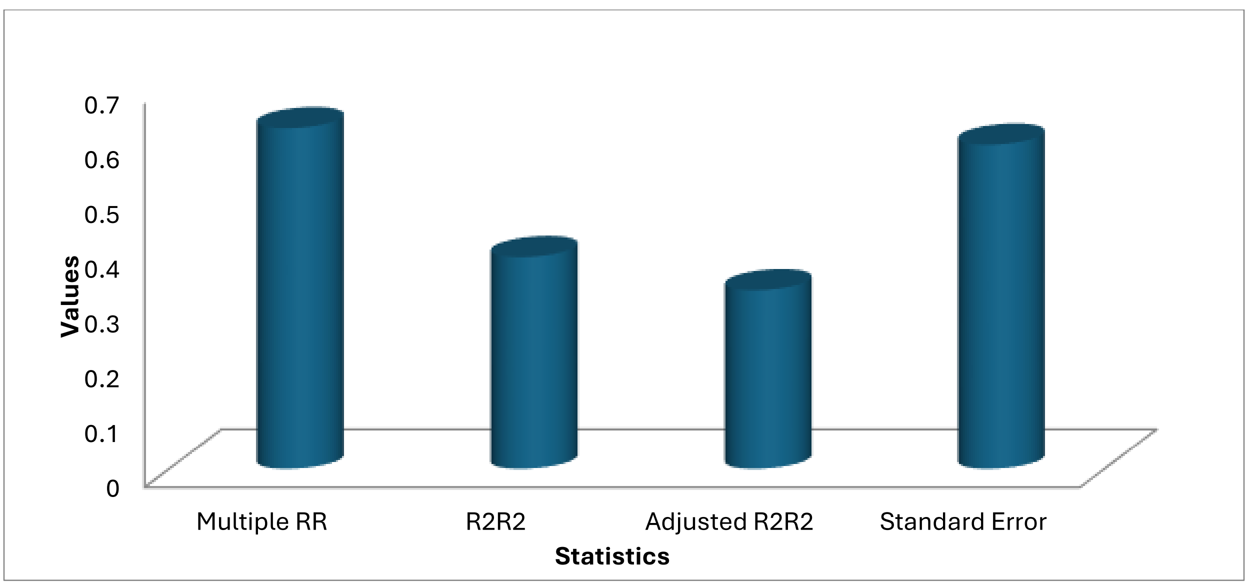

Figure 3: Regression Statistics

The variables of education, occupation, and job duration are strong predictors of Consumer Risk Rating, with p-values less than 0.05. Age and landline status are marginally significant, whereas gender, marital status, dependents, and net income are not statistically significant.

Table 7: The Regression Analysis for the Consumer Risk Rating

Variable	Coefficients	SE	T-Stat	P-Value
Intercept	8.218	0.681	12.08	0.001
Gender	0.212	0.292	0.730	0.467
Marital Status	0.094	0.451	0.210	0.836
Dependents	–0.005	0.051	–0.101	0.921
Age	–0.021	0.013	–2.001	0.049
Education	0.344	0.076	4.541	0.001
Occupation	0.708	0.243	2.912	0.005
Net Income	0.123	0.335	0.778	0.446
Length of Job	0.037	0.011	3.495	0.001
Landline	0.433	0.219	1.985	0.051

Note: N=100, DV: Consumer Risk Rating (CRR) Model fit: R2=0.387, adjusted R2 = .326, Estimate = 0.592.

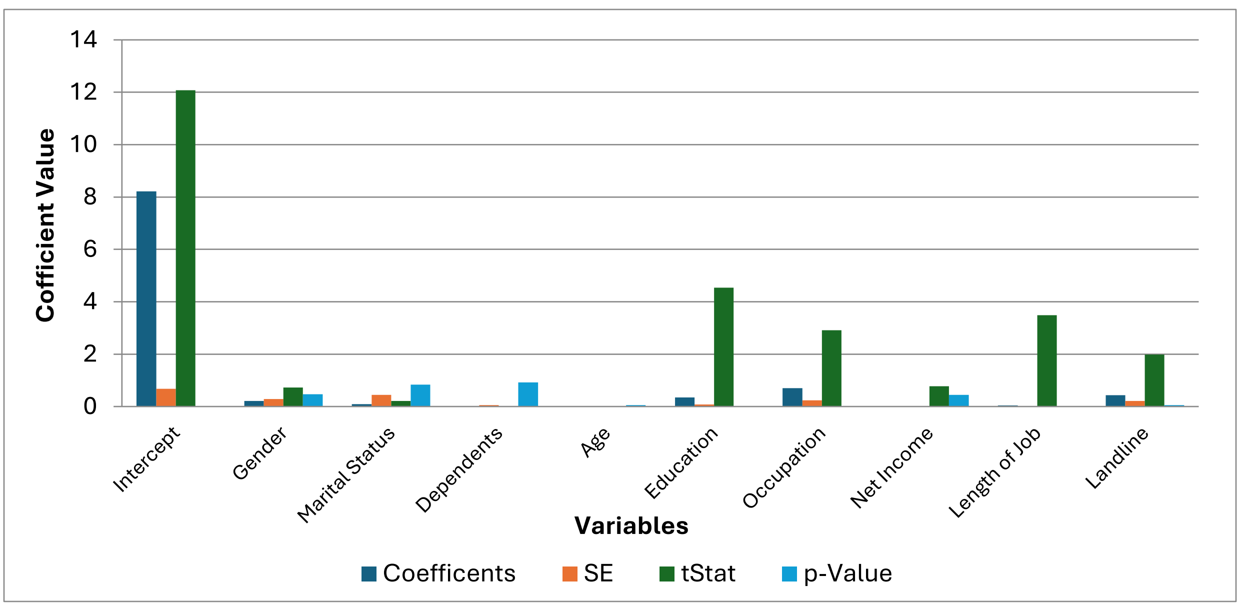

Figure 4: The Regression Coefficients for Consumer Risk Ratings

The regression model in Table 7 shows that Consumer Risk Rating has an intercept level of 8.218 when all other independent variables are zero ($p < .001$). Education, occupation, and job duration are significant predictors of CRR. Education increases CRR by 0.344 ($p < .001$), occupation increases CRR by 0.708 ($p = .005$), and job duration increases CRR by 0.037 ($p = .001$). Age has a slightly negative effect (coefficient = -0.021, $p = .049$), while landline status is marginally significant (coefficient = 0.433, $p = .051$). Gender, marital status, dependents, and net income are not statistically significant. Therefore, education, occupation, and employment tenure are the strongest predictors of CRR in this sample.

The findings support that socio-economic attributes such as educational background, job type, and employment tenure are important factors in predicting credit risk, as found in previous empirical studies on borrower-specific factors that influence default risk. These results support the alternative hypothesis that some selected socio-economic variables are significantly associated with CRR and probability of default. For Islamic banking, the findings confirm the need to include non-financial, borrower-level factors in credit risk models since the use of financial measures only may ignore other important risk factors. Thus, this study offers insights for improving current Islamic credit risk rating practices by taking into account socio-economic factors with the aim of improving the accuracy, reliability, and Shariah-compliant risk management in Islamic consumer loans.

CONCLUSION

This article examined the validation of meaningful credit variables in an Islamic consumer portfolio, based on a simple random sample of 100 cases drawn from 2,076 cases of Public Sector Bank. The analysis followed the logic of credit risk modeling in earlier studies and applied correlation, OLS regression, and probit regression to examine whether the bank's risk rating system and borrower-level socio-economic indicators explain credit performance.

Furthermore, the results of the linear model reveal that 38.71 percent of the variation in Consumer Risk Rating is explained by education, occupation, job duration, and age. Gender, marital status, dependents, and net income are statistically insignificant in the OLS model. The binary probit model shows that higher CRR significantly reduces default probability, while marital status is marginally significant. Therefore, the alternative hypothesis is partially supported: selected socio-economic variables, especially education, occupation, and job duration, are significantly related to CRR, while CRR and marital status are relevant for default probability.

Future Research Insight

Due to the limited availability of data, this study is restricted to the consumer portfolio of one public sector bank. The randomly selected sample provides useful exploratory evidence, but it is not fully representative of the Islamic banking industry in Pakistan. Future research should use larger samples from multiple Islamic banks and compare different products, such as Murabaha, Ijarah, and Diminishing Musharakah.

Policy Recommendations on current situations

The empirical findings of the study offer policy insights. Since education, occupation and tenure were found to be important factors in predicting credit risk, Islamic banks should incorporate these socio-economic indicators more effectively in their credit risk rating systems to better predict default. Policymakers, especially the State Bank of Pakistan, can enhance guidelines for regulation by promoting the incorporation of individual socio-economic indicators with financial risk indicators in credit risk models.

Moreover, the importance of CRR in forecasting consumer default implies that banks should emphasis on the validation and periodic review of their rating systems to ensure that they reflect borrower behavior. Such alterations can facilitate better risk-based pricing, Shariah-compliant nature of consumer financing, credit allocation, improve the competence and constancy.

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