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Factors Affecting Formal Micro-Credits in the Wetland Regions of Bangladesh: A Discriminant Analysis

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Abstract

Micro-credit has been playing a vital role in developing wetland people’s socio-economic status by facilitating their income-generating activities such as seasonal fish farming, raising ducks and cattle, and floating vegetable gardens. Wetland people’s livelihoods are largely dependent on borrowing micro-credits, but access to formal credits is somewhat intricate for them due to procedural complexity. Therefore, this study aims to explore the potential discriminating factors of formal credits in the wetland region of Bangladesh. This study used data from 1607 micro-credit receiver households that were collected by a research project sponsored by the GARE Program, Ministry of Education, Government of Bangladesh. The discriminant analysis was performed to explore the factors discriminating between formal and informal credit-receiving groups. This study considered three types of factors such as borrower’s individual-level, household-level, and micro-credit related characteristics as the potential factors distinguishing between formal and informal credits. The findings show that micro-credit-related factors such as the number of installments, duration of the loan, and rate of interest are more crucial for affecting formal credit in the wetland peoples of Bangladesh. Most vulnerable groups in the wetland region still struggle to obtain formal credit because of obstacles such as a lower number of installments, lower duration of loans, and high interest rates. The government policy should remove these obstacles to ensure the people's easy access to formal loans, which would ultimately improve their socio-economic conditions.

Keywords: Formal and informal micro-credits, Discriminant analysis, Wetland region, Bangladesh.

AMS Classification: 62H99, 91B28, 91B82.

1. Introduction

A wetland is a location that experiences periodic or permanent flooding with shallow water, with the water remaining at or close to the surface[1]. Bangladesh has a variety of wetlands, including floodplains, *haors* (seasonal water bodies), *baors* (oxbow lakes), *beels* (perennial water bodies), and so on (MOWR, 2016). *Haor* is a bowl-shaped appearance that gathers surface runoff water during monsoon. Bangladesh’s *haor* districts comprise 19,998 square kilometers or 13.56% of the

[1] The Bangladesh Water Act, 2013, Section 2(6)

country's total land area (CEGIS, 2012). About 43% (8585 sq. km.) of the entire area of *haor* districts is made up of wetlands, comprising 373 *haors* (CEGIS, 2012). The government of Bangladesh's Department of Environment reported that the *haor* region produces 5.25 million tons of paddy annually (Ali et al., 2018). Despite being one of the main areas for economic production in the nation, the *haor* area is still underdeveloped because of its physical and hydrological conditions (Chowdhooree et al., 2020). *Haor* peoples also differ greatly from the nation's overall population in terms of income, consumption, poverty, and other factors (Khondker and Mahzab, 2015). The area's diversified economic resources are primarily derived from agriculture and fisheries (Haroon and Kibria, 2017). Due to floods and other natural calamities, individuals who are involved in agriculture and fisheries are frequently unemployed which causes poverty in these places and occasionally leads to famine-type situations. The lengthy seasonality of the rainy season also contributes to the *haor* people's unemployment (HILIP, 2011). When no earnings come in, people rely on high-interest loans from local money lenders and micro-credit organizations to make ends meet (Amin and Farid, 2005).

The micro-credit program is considered an effective anti-poverty tool for the people of Bangladesh (Micro-Credit Summit, 1997). It is a technique that involves giving a very small loan to poor people to support their small-scale business endeavors (Uddin, 2011). Chowdhury et al. (2005) defined micro-credit as the distribution of small institutional loans without collateral to mutually liable poor people for their self-employment. The types of micro-credits received by the people living in Bangladesh's wetlands have been categorized as formal and informal. Formal credits are those provided by government (banks/cooperatives) and non-government (MFI/NGO/insurance) organizations. On the other hand, informal credits are provided by local moneylenders such as *Mahajan, private samittee*, relatives, friends, neighbors, and land owners. Immediately after the independence of Bangladesh, the first interest-free and collateral-free micro-credit scheme was launched in 1974 as part of the Rural Social Services (RSS) program to improve the condition of the country's marginalized population (MRA, 2023). Dr. Yunus founded the Grameen Bank in 1983, and around 70 countries have since embraced the micro-credit concept (Hossain and Knight, 2008). Micro-credit has been gaining popularity for a few decades, especially in light of the Grameen Bank's success in Bangladesh. Hashemi and Morshed (1997) pointed out that in addition to reducing poverty, the Grameen Bank improves borrowers' standards of living and strengthens their ability to sustain a steady income over time. So Bangladeshi government has been endeavoring to lessen poverty among its citizens and to reach the SDGs goal through micro-credits. Several NGOs are also giving micro-credits to the poor in an effort to increase their income and alleviate their miserable situations (Hashemi et al., 1996; Hossain, 1988; Yunus, 1999). According to the MRA (2020), there are around 40 million micro-credit recipients in Bangladesh, and there are Taka 1696.24 billion amount of outstanding loans. The formal sector provides over half of the credit through microfinance institutions (MFIs) and the informal sector provides the remaining portion of the loan. Loans from the formal sector require collateral. However, when it comes to the informal sector, credit services are offered to extremely poor households without the need for collateral or outside guarantees (Mujeri, 2015). The wetland people's credit behavior revealed that informal credit is more popular than formal credit, and local moneylenders are the primary sources of informal loans (Kazal et al., 2010). However, it is alleged that the *Mahajans* and the landowners had been charging exorbitant interest rates on the money they lent out and, hence, are marked as 'usurious monopolists' (Hossain and Bayes, 2009). Due to poverty, most *haor* people depend on borrowings from local moneylenders for their livelihood. A study documented that about 80% of *haor* people borrowed money from different sources, and

59% borrowed it to purchase food (Kazal et al., 2017). The interest rate of different types of micro-credits varied from 12.5% to 43%, which rose to 110% in some cases for informal loans (Institute of Microfinance, 2015).

To popularize formal credit among the wetland population and ensure easy access to it, a quick investigation is required to determine the factors that differentiate formal credit from informal ones. That is, it is essential to investigate which factors are responsible for receiving formal credits. Hence, this study aims to explore the factors affecting formal micro-credits in Bangladesh's wetland regions. The study's main contribution is to identify factors underlying formal credits and to suggest necessary steps for their easy access. Discriminant analysis has been applied to identify conglomerate targets (Zanakis, 1994), predict bond ratings (Michel, 1977; Pinches, 1973), and corporate bankruptcies (Altman, 1968). However, studies using discriminant analysis to identify factors affecting micro-credits have rarely been seen. Therefore, this study applied discriminant analysis to fill this research gap and to achieve the research objective. The structure of this paper is as follows: Section 2 provides materials and methods, including study area, data, discriminant analysis approach, and variables descriptions. The results and discussions are presented in Section 3. The conclusions and policy implications are presented in Section 4.

2. Materials and Methods

2.1 Study Area

This study was conducted in Bangladesh's wetland region, covering six *haor*-prone districts such as Sunamganj, Sylhet, Habiganj, Maulvibazar, Netrokona, and Kishoreganj. *Haors* are mainly concentrated in four districts, viz., Sunamganj, Sylhet, Netrokona, and Kishoreganj. There are seven *haor* prone districts according to the CEGIS (2012). Six districts cover almost all the *haors* (366 *haors*/wetlands) except 7 in the Brahmanbaria district. This study considered six districts because most of the *haors* are located in these districts.

2.2 The Data

This study used the data collected through a household survey by the research project "Vicious Cycle of Poverty in *Haor* Region of Bangladesh: Impact of Formal and Informal Credits," funded by the Grants for Advanced Research in Education (GARE) Program, Ministry of Education, Government of Bangladesh. The household survey was conducted during February–December 2019. A cluster-sampling design was used in the survey and *haor* attached *mouzas* were considered as clusters. The household survey collected data from 1607 micro-credit recipients and 733 non-recipient households. Among the micro-credit recipient households, 1158 were found to receive credits from formal sources, and 449 from informal sources. Formal credit receivers were identified as those who received loans from the government and non-government organizations and informal credit receivers were identified as those who received loans from local money lenders. This study took several steps to check the validity and reliability of the data. Among them, cross-checks of filled-up interview schedules by supervisors and examination of the validity of the variables by data exploration are noted.

2.3 Discriminant Analysis Approach

The multivariate classification approach known as discriminant analysis was introduced first by R. A. Fisher in 1936. Its two primary goals are to distinguish among or divide into groups and to determine which group an object is a member of out of several predetermined groups (Fuentes, 2011). To determine the pertinent factors that are crucial for differentiating between the selection of micro-credit benefits from formal and informal sources, this study used a two-group discriminant analysis. The process entails determining a variate, which is a linear combination of more than one explanatory variables that provide the highest degree of discrimination between predetermined groups (Walde, 2014). In order to achieve discrimination, the weight or coefficient of each variable is chosen to maximize the variance between groups as compared to the variance within groups. The following equation provides the required linear combination, which is also called Fisher's linear discriminant function:

$$D = a_0 + a_1 X_1 + a_2 X_2 + ... + a_n X_n \qquad (1)$$

Where, D is the discriminant score.

a_0 is the constant term in discriminant function.

$a_1, a_2, ..., a_n$ are the *n*-discriminant coefficients or weights of explanatory variables.

$X_1, X_1, ..., X_n$ are the *n*-explanatory variables in the discriminant function.

Equation (1) provides a suitable way for categorizing a person who is expected to obtain credit from a formal or informal source based on some characteristics. A variety of statistical methods, including Wilks' lambda, Mahalanobis' distance, and classification by maximum likelihood can be used to carry out discriminant analysis. In this work, the Wilks' lambda approach was utilized to perform discriminant analysis.

2.4 Description of Variables

This study's variables have been classified into two categories: explanatory and outcome. The discriminant analysis demands that the explanatory variables should be either an interval or ratio scale and the categorical explanatory variable that cannot be transformed into an interval or ratio scale should be removed from the analysis. This study considered micro-credit type as an outcome variable and three types of characteristics as explanatory variables. These are borrower's individual level characteristics (age of loan receivers), their household level characteristics (number of earning members, dependency ratio, annual income, amount of land, amount in the family business, number of furniture, number of fishing nets), and their micro-credit related characteristics (loan amount, loan duration, number of installment, rate of interest). Table 1 provides a thorough explanation of each variable.

Table 1: List of Variables, Their Description and Type

Variables	Description	Type
Explanatory variables		
Age	Age of loan receivers (in years)	Numeric
Earning members	Number of earning members in a borrower household	Numeric
Dependency ratio	Dependency ratio in a borrower household	Numeric
Amount of loan	Borrower's total amount of loan (in Taka)	Numeric
Duration of loan	Duration of loan received (in month)	Numeric
Installment	Number of installments	Numeric
Interest rate	Rate of interest of received loan (in percentage)	Numeric
Annual income	Total annual income (in Taka)	Numeric
Amount of land	Total amount of land (in decimal)	Numeric

Variables	Description	Type
Family business	Amount in the family business (in Taka)	Numeric
Furniture	Number of furniture in the drawing room	Numeric
Fishing net	Number of fishing nets	Numeric
Outcome variable		
Micro-credit type	Type of micro-credit (Formal, Informal)	Categorical

Since all the explanatory variables are numerical and the outcome variable is categorical, discriminant analysis is the right choice for differentiating between formal and informal credit sources.

3. Results and Discussions

3.1 Group Statistics of the Predictors

The group statistics are computed to initially screen which factors discriminate between formal and informal credit sources.

Table 2: Predictor's Group Means and Standard Deviations

Predictors	Group means		Group standard deviations	
	Formal	Informal	Formal	Informal
Age	41.80	44.19	11.28	11.45
Earning members	1.59	1.82	1.00	1.05
Dependency ratio	0.75	0.81	0.58	0.73
Amount of loan	34596.29	45474.61	40825.63	76125.59
Duration of loan	11.86	21.25	3.51	22.80
Installment	29.30	7.29	16.88	9.02
Interest rate	17.77	26.0	7.55	19.12
Annual income	105281.49	96233.18	58972.96	59387.91
Amount of land	67.29	80.75	112.39	112.20
Family business	8088.08	2244.99	49980.38	14219.03
Furniture	0.13	0.25	0.64	0.85
Fishing net	0.27	0.45	0.73	0.89

The group means shows that the variation between formal and informal credit receiving households is larger when it pertains to the loan amount, loan duration, number of installments, rate of interest, annual income, and amount in the family business (Table 2). The group standard deviations also seem to indicate that formal and informal credit receiving households are spread more widely with respect to the loan amount, loan duration, number of installments, rate of interest, and amount in the family business (Table 2). That is, there was more variation between the groups when it came to loan-related characteristics. This finding primarily indicates that loan-related factors may have a greater impact on discriminating between formal and informal credit sources.

3.2 Descriptive Measures of Multicollinearity

Multicollinearity is a problem in estimation or making conclusions when discriminating the choice of receiving formal and informal credits. The descriptive measure of multicollinearity is the linear relationship between predictors, which is determined by computing the correlation matrix.

Table 3: Correlation Matrix of Predictors

Predictors	01.	02.	03.	04.	05.	06.	07.	08.	09.	10.	11.	12.
01. Age	1.00											
02. Earning members	0.22	1.00										
03. Dependency ratio	-0.24	-0.18	1.00									
04. Amount of loan	0.07	0.14	0.00	1.00								
05. Duration of loan	0.03	0.25	0.09	0.30	1.00							
06. Installment	-0.01	-0.01	-0.04	-0.05	0.12	1.00						
07. Interest rate	-0.03	0.03	0.04	0.17	0.16	-0.04	1.00					
08. Annual income	0.16	0.20	-0.09	0.23	0.10	0.09	-0.07	1.00				
09. Amount of land	0.18	0.14	-0.00	0.09	0.06	-0.05	-0.07	0.21	1.00			
10. Family business	-0.01	-0.00	-0.03	0.09	0.02	0.06	-0.01	0.03	-0.01	1.00		
11. Furniture	0.06	0.06	-0.06	-0.02	-0.07	0.11	-0.09	0.14	0.03	-0.00	1.00	
12. Fishing net	-0.03	0.09	-0.02	0.00	0.05	0.12	-0.01	0.09	-0.04	0.00	0.17	1.00

The correlation matrix shows a very weak correlation among predictors, with an estimated correlation coefficient for each set of pairs below 0.31 (Table 3). Therefore, the explanatory variables included in the discriminant model do not show any signs of multicollinearity.

3.3 Summary of Canonical Discriminant Functions

In discriminant analysis, a smaller Wilks' lambda value indicates the explanatory variable is more important to the discriminant function. When predictors are analyzed separately, the significance of the F-statistic shows if there is a significant difference between the households who received credit from formal and informal sources based on predictors.

Table 4: Tests of Equality of Group Means

Predictors	Wilks' lambda	F-value	df1	df2	P-value
Age	0.991	14.409	1	1605	<0.001
Earning members	0.990	15.424	1	1605	<0.001
Dependency ratio	0.998	2.895	1	1605	0.089
Amount of loan	0.992	13.582	1	1605	<0.001
Duration of loan	0.897	185.231	1	1605	<0.001
Installment	0.700	687.210	1	1605	<0.001
Interest rate	0.913	153.155	1	1605	<0.001

Predictors	Wilks' lambda	F-value	df1	df2	P-value
Annual income	0.995	7.587	1	1605	0.006
Amount of land	0.997	4.648	1	1605	0.031
Family business	0.996	5.948	1	1605	0.015
Furniture	0.995	8.478	1	1605	0.004
Fishing net	0.989	18.140	1	1605	<0.001

Table 5: Test of Significance of Overall Function

Model summary	Wilks' lambda	Chi-square	df	P-value
Test of function	0.596	826.193	12	<0.001
Eigenvalue		0.676		
Canonical correlation		0.635		
R^2 from canonical correlation		0.403		

From Table 4, the average dependency ratio was found to significantly differentiate the formal and informal loans at a 10% significance level. Additionally, the formal and informal loans differ significantly at a 5% significance level in terms of the average value of the amount of land and amount in the family businesses. The remaining predictors, however, significantly differentiate between the formal and informal credit groups at a 1% or less than 1% significance level. Here, each of Wilks' lambda is significant by F-statistic, allowing us to incorporate all the explanatory variables into our discriminant model. However, the number of installments with a lower Wilks' lambda (0.700) holds greater significance in discrimination. The results of this test validate the next step of discriminant analysis. It is possible to estimate only one discriminant function using all of the predictors because there are two groups.

Wilks' lambda offers a test for testing the null hypothesis that the vector of predictor means is the same in formal and informal credit groups. The percentage of discriminant scores' total variation that cannot be explained by group differences is known as the lambda coefficient, and in this case, it is 59.6% (Table 5). The formal test (Chi-square (12) = 826.193, $p<0.001$) confirms that the set of twelve means of predictors differs significantly between the two groups. Therefore, it may be concluded that the discriminant function is significant and may be used for further interpretation.

The fundamental rule of discriminant function estimation is that the variance between groups in relation to the variance within a group should be maximized. The variance between groups to the variance within a group is known as Eigenvalue. An Eigenvalue provides the proportion of explained variation and it should always be as large as possible. With the discriminant function, the estimated eigenvalue is 0.676, meaning that 100% of the explained variation is accounted for. The canonical correlation, or the simple correlation coefficient between the discriminant score and the related group membership (formal/informal), is calculated as 0.635. The ability to fit a model is demonstrated by the square of the canonical correlation. The R^2 value of 0.403 concludes that 40% of the variation in credit type is due to the variation in twelve predictors.

3.4 Estimation of Two-Group Discriminant Analysis

A variable's estimated coefficients rely on other variables that are part of the analysis. The impact of the resultant variable is indicated by the sign of the coefficients. The unstandardized coefficients are the list of coefficients of the unstandardized discriminant function. A larger unstandardized coefficient indicates a more robust predictor for discrimination. The reason for the estimation of standardized coefficients is that some predictors were found in distinct units. A relatively larger standardized coefficient also indicates a higher discriminating ability of the function.

Table 6: Estimates of Two-Group Discriminant Analysis

Discriminating variables[a]	**Unstandardized coefficients**[b]	**Standardized coefficients**[c]	**Structure matrix**[d]
Installment	-0.055	-0.829	-0.796
Duration of loan	0.034	0.417	0.413
Interest rate	0.026	0.313	0.376
Fishing net	0.247	0.192	0.129
Earning members	-0.035	-0.035	0.119
Age	0.010	0.118	0.115
Amount of loan	0.001	-0.089	0.112
Furniture	0.290	0.205	0.088
Annual income	0.001	-0.067	-0.084
Family business	0.001	-0.017	-0.074
Amount of land	0.001	0.023	0.064
Dependency ratio	0.007	0.005	0.052
Constant	**-0.090**	-	-

[a]Discriminating variables are ranked according to the degree of correlation to find the greatest contributor.
[b]Coefficients are calculated from unstandardized predictors utilizing canonical discriminant functions.
[c]Coefficients are calculated from the standardized predictors utilizing canonical discriminant functions.
[d]Pooled within-group correlations between discriminating variables and canonical discriminant functions.

From Table 6, the standardized coefficients of the model indicate that loan-related factors such as the number of installments, duration of loan, and rate of interest are best suited for discriminating between formal and informal credit groups. That is these factors are more likely to result in the wetland household receiving formal credit. Although other predictors are significant, their factor loadings of less than 0.30 indicate their least contribution to discrimination (Yakubu et al., 2017). The discriminant loadings or canonical loadings quantify the correlation between predictors and canonical discriminant functions that are shown in the structure matrix column of Table 6. These loadings determine which predictor, out of all the others, is most crucial for differentiating the micro-credit borrowing sources. Here, “the number of installments” is the most powerful predictor in differentiating between formal and informal credit groups, followed by the loan duration, and rate of interest. On the other hand, the least contributory but still significant predictors for differentiating the borrowing sources of credit include dependency ratio, household’s land possession, amount in the family business, household’s annual income, number of furniture, amount of loan, age of loan receivers, number of earning members, and number of fishing nets.

3.5 Estimation of Fisher’s Linear Discriminant Function

In order to distinguish between formal and informal credit sources based on predictors, this study determines the parameters of Fisher’s discriminant function.

Table 7: Estimates of Fisher's Linear Discriminant Function

Predictors	**Informal**	**Formal**	**Fisher's discriminant function coefficients**
(Constant)	-15.950	-14.098	-0.090
Age	0.375	0.356	0.010
Earning members	0.824	0.888	-0.035
Dependency ratio	3.903	3.889	0.007
Amount of loan	<0.001	<0.001	0.001
Duration of loan	0.063	0.002	0.034
Installment	0.033	0.134	-0.055
Interest rate	0.187	0.139	0.026
Annual income	<0.001	<0.001	0.001
Amount of land	-0.002	-0.002	0.001
Family business	<0.001	<0.001	0.001
Furniture	0.262	-0.269	0.290
Fishing net	0.635	0.183	0.247
General classification rule			
Functions at group centroids	1.320	-0.512	**0.404**

Based on the coefficients, the estimated Fisher's linear discrimination function is given by:
D = -0.090 + 0.010×Age - 0.035×Earning members + 0.007×Dependency ratio + 0.001×Amount of loan + 0.034×Duration of loan - 0.055×Installment + 0.026×Interest rate + 0.001×Annual income + 0.001×Amount of land + 0.001×Family business + 0.290×Furniture + 0.247×Fishing net

From Table 7, functions at group centroids (average of group means) are found as 0.404. It follows that new members who have discriminant scores D higher than 0.404 are expected to receive loans from informal sources otherwise they would like to receive loans from formal sources.

3.6 Classification Statistics

In discriminant analysis, the cross-validation technique is used to obtain the model validation. This technique is called the leave-one-out cross-validation method. This method estimates the hit ratio, or percentage of correctly classified data to show that the discriminant analysis was validated. The distribution of observations among the credit groups is known as the prior probabilities for groups and is used as a starting point for the analysis.

Table 8: Validation of Model in Discriminant Analysis

Prior probabilities for groups (informal = 0.279, formal = 0.721)					
No cross-validation[a]	Credit type		Predicted: Informal	Predicted: Formal	Total
	Observed	Informal	257	192	449
		Formal	29	1129	1158
Leave-one-out cross-validation[b]	Credit type		Predicted: Informal	Predicted: Formal	Total
	Observed	Informal	255	194	449
		Formal	29	1129	1158

[a]Hit ratio of 0.862 measures that 86.2% of actual grouped cases are accurately classified.
[b]Hit ratio of 0.861 measures that 86.1% of leave-one-out cross-validated grouped cases are accurately classified.

The hit ratio indicates that the leave-one-out cross-validation does not substantially improve over the no cross-validation. About, 86% of the actual grouped cases are accurately classified by the discriminant model according to no cross-validation technique. This implies that the estimated model performs quite well in differentiating between the credit sources of Bangladesh's wetland peoples.

4. Conclusions and Policy Implications

This study intends to explore the factors affecting formal micro-credits in Bangladesh's wetland regions by performing a two-group discriminant analysis. The findings of this study conclude that loan-related factors such as the number of installments, duration of the loan, and rate of interest are the most discriminating factors between formal and informal credits in the wetland regions of Bangladesh. The other factors such as the number of fishing nets, number of earning members, age of loan receivers, amount of loans, number of furniture, annual income, amount in family business, amount of land, and dependency ratio are also found significant with a factor loading 0.30 or less, indicate that these factors have a poor contribution to discriminate between formal and informal micro-credits. Loan-related obstacles such as a lower number of installments, lower duration of the loan, and high interest rates sometimes make it impossible for the most vulnerable people to receive loans. Therefore, government policy should focus on removing these obstacles to ensure the people's easy access to formal loans, which would eventually ensure their socio-economic well-being. A study can be undertaken to explore the role of households' poverty conditions in accessing formal loans in addition to the factors identified by this study.

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