JOURNAL OF CRITICAL REVIEWS

ISSN- 2394-5125 VOL 8, ISSUE 02, 2021

Factors affecting the probability of defaulting facilities of Melli Bank's agricultural legal clients (case study: Provinces of Khorasan)

Javid Karimzadeh[1], Mahmoud SabouhiSabouni*[2], Hossein Mohammadi[3], Mahmoud DaneshvarKakhki[4], Mohammad Ghorbani[5]

Abstract

This study aims to investigate determinants of the probability of default on agricultural facilities granted to 286 companies during the years 2007 to 2017. Logit, Probit, and C-Log-Log models have been used for this purpose. The variables included the relevance of the CEO's field of study; a single beneficiary company, domestic production of raw materials and Altman Z- score or company's financial strength. The results reveal the high validity and strength of the Probit model, as it can predict and classify observations with high probability of default with 96% accuracy and observations with low probability of default with 92% accuracy, which can demonstrate the validity of the model. The results also show that the probability of default is chiefly affected by a company's financial strength. Therefore, in order to significantly reduce the probability of default in repayment of the facilities granted by customers, greater attention should be allocated to the financial strength of companies at the time of granting facilities.

Keywords: default of facilities Logit model, Probit model, C-Log-Log model, Financial strength, Bank Melli

Introduction

A performance review of countries reveals that states that have an efficient model of capital allocation in place often enjoy a higher level of economic progress and consequently higher social welfare. The investment resources are allocated through the financial market, including the banking credit market. As a crucial role of the bank in the financial market, it is undertaken by providing credit to customers. One major customer of banks is the agricultural sector. One of the fundamental economic sectors of the country, agricultural sector accounts for 14.2 of the value added of the entire Iranian economy according to the latest national accounts data provided by the Central Bank in 2017 (Central Bank's economic indices). Hence, it is essential to pay a greater attention to this sector due to the heavy reliance of the country's economy on oil resources. It seems that the agricultural sector has potentials and comparative advantages to meet the economic demands of the country. It should be noted that due to the characteristics of agricultural sector such as seasonal agricultural production and exposure to risk and uncertainty, receiving credits and entering agricultural financial markets, andconsequently the repayment of such credits, are subject to climate change. Such characteristics differentiate the agricultural sector from other sectors, putting the financing of this sector under spotlight. Agriculture is often seen as one of the most important sectors in terms of production, but the capital formation in this sector is not proportionate to its performance and capacity and has fallen behind other sectors (Ghorbani and Nemati, 2011). Also, given the small savings of most farmers, an important way through which farmers raise the required capital is bank loans. Facilities granted to the agricultural sector represent one of the variables that can bolster the country's economic growth by increasing the value added of the agricultural sector. Therefore, credits, if appropriated optimally, will eradicate one of the major obstacles to the growth and

[1] . Phd student of Agricultural Economics Department, Agriculture Faculty, Ferdowsi University of Mashhad, Iran j.karimzadeh1124@gmail.com phone:+989188140401

[2] . Professor of Agricultural Economics Department, Agriculture Faculty, Ferdowsi University of Mashhad, Iran Sabouhi@um.ac.ir phone:+989151114327

*Correspondingautor

[3] . Associate Professor of Agricultural Economics Department, Agriculture Faculty, Ferdowsi University of Mashhad, Iran

hoseinmohammadi.um@gmail.com phone: +989151025098

[4] . Professor of Agricultural Economics Department, Agriculture Faculty, Ferdowsi University of Mashhad, Iran daneshvar@um.ac.ir phone: +989155013517

[5] . Professor of Agricultural Economics Department, Agriculture Faculty, Ferdowsi University of Mashhad, Iran Ghorbani@um.ac.ir phone: +989155174384

ISSN- 2394-5125 VOL 8, ISSUE 02, 2021

development of the agricultural sector, i.e. the insufficient financial resources, improve the performance of agricultural production inputs and consequently increase the added value of the agricultural sector (SharifiRenani et al.2013).

Accordingly, in recent years, the demand for agricultural credit has surged sharply, but financial institutions have faced a number of challenging problems. One of the problems of agricultural credits in Iran is the gap between supply and demand for loans, imbalance in the distribution of bank facilities, reliance on government subsidies, and non-repayment of low-fee bank facilities (Ronaghi and Bakhshudeh, 2014). Agricultural credit in Iran is mainly provided by informal credit sources (sources that do not operate within the framework of government laws and regulations) including local loan sharks, brokers, friends and relatives, and official credit sources including Agricultural Banks, rural cooperatives and commercial banks such as Melli and Saderat, etc.). The facilities granted by financial institutions is intended to boost production, moderate income, facilitate the adoption of optimal agricultural practices, compensate for natural disasters, and meet social expectations, among other things (Bagheri and Najafi, 2004). Given the fact that timely repayment of credit is vital to the survival of credit institutions, and especially considering the high rate of non-repayment in bank providing agricultural facilities, and the heavy reliance of the bank's financial resources on the repaid credit, it is essential to investigate factors that influence the repayment and non-repayment of agricultural facilities. Therefore, a critical issue is to assess credit risk (i.e. the probability of default on repayment of facilities). Risk mitigation and control, as one of the key determinants associated with the improvement of credit allocation process, plays a pivotal role in providing facilities.

As noted earlier, overdue receivables are a serious problemfacing most financial institutions, including Bank Melli. Given the information asymmetry between the recipients of facilities in the agricultural sector from Bank Melli and based on statistics reported by Bank Melli, in a ten-year period (2007-2017), on average 15 to 20% of facilities granted to the agricultural sector have not been repaid or have several overdue installments (Bank Melli's house organ No. 278). Obviously, as the amount of default or deferment in the repayment of agricultural facilities increases, the bank's resources to grant agricultural facilities will be curtailed and farmers applying for micro-facilities or companies requesting macro facilities would have trouble accessing these resources. Therefore, studying determinants of the probability of default in agricultural sector before granting facilities in the agricultural sector can decrease overdue facilities in this sector. Furthermore, Bank Melli can draw on these resources to grant more facilities to applicants in this sector. This can contribute to the development and improvement of the agricultural sector. According to the latest surveys (at the end of 2017), 47% of the facilities granted by Bank Melli in the agricultural sector were received by legal entities and 53% by natural entities. Also, 38% of the facilities in the agricultural sector are granted to the agriculture, 15% to the horticulture, 33% to the livestock farming, and 14% to the poultry farming (Bank MelliHouse Organ No. 279). This study focuses on legal recipients of facilities with financial statements because it is assumed that the financial ratios extracted from the financial statements are particularly important in evaluating the financial status of a company. In this study, 286 agricultural companies receiving facilities from Bank Melli (in KhorasanRazavi, North Khorasan and South Khorasan provinces) were selected. The facilities allocated to these companies account for 38% of the total facilities granted to legal entities in the agricultural sector of these three provinces. In total, over a ten-year period (2007-2017), 15 and 20% of the facilities granted in the agricultural sector are either not paid or have several deferred installments. Accordingly, between 7 and 9% of the total arrears in the agricultural sector is related to legal recipients of facilities. Therefore, this paper aims to explore the determinants of legal entities' default on repayment of the facilities granted by Bank Melli to the agricultural sector in KhorasanRazavi, North Khorasan and South Khorasanprovinces. The statistical population of this research consists of medium and large-sized companies in the agricultural sector that have received facilities from the Bank Melli in KhorasanRazavi, North Khorasan and South Khorasan provinces between 2007-2017. It comprised 1395 companies in the agricultural sector, of which 286 were selected using simple random sampling method. Therefore, the sample includes 286 corporate files selected from available files in these three provinces. Large and medium-sized companies were considered as a statistical population because they had audited financial statements, and the ratios and financial information extracted from the financial statements in most studies had a bearing on the probability of default. Therefore, the purpose of this study was to assess the probability of default on repayment of facilities granted by Bank Melli to legal entities in the agricultural sector (in KhorasanRazavi, North Khorasan and South Khorasan provinces). Informed by this goal, the research hypothesis is as follows:

There is a significant relationship between financial ratios (ownership, current and debt) in the studied companies and the probability of default on repayment of facilities received from Bank Melliin KhorasanRazavi, North Khorasan and South Khorasan provinces.

ISSN- 2394-5125 VOL 8, ISSUE 02, 2021

Research background

Studies abroad

Brehanu and Fufa (2008) used a two-stage Tobit model to analyze the facility repayment rate of small semi-official financial institutions in Ethiopia. Based on the results, the size of the allocated lands, the total number of livestock, the history of using agricultural development services, expert supervision and off-farm income were identified as significant factors in repayment rate of the facility.

Using Logit and Tobit models, Adegbite (2009) investigated the determinants of the agricultural facility repayment in the Ogun region of Nigeria. The results suggested that the loan sum, payment delay, farm distance from the bank, age, knowledge and experience of the farmer, natural damages, ests and diseases had a significant effect on the repayment of facilities.

Acquah and Addo (2011) studied the factors impacting the loan repayment performance of fishermen in Ghana using multiple regression model. The results revealed that 70% of fishermen were late on the payment of loans and factors such as experience, income, literacy and loan sum have a positive impact and age and investment have a negative effect on loan repayment.

Wongnaa and Vitor (2013) explored the determinants of improved loan repayments by potato growers in Ghana using the Probit model. Based on the results, age, literacy, experience, off-farm income had a positive effect on loan repayment performance and gender and marital status had a negative effect on repayment performance.

Sylvester et al. (2013) examined the loan repayment performance of palm oil producers and processors in Nigeria using multiple regression. The results reflected that the loan size is affected by the experience of processors, annual gross income, investment rate, and the ratio of asset turnover,with the distance from the lending institution influencing the loan repayment rate.

Espinoza and Prasad (2010) in a study on deferred receivables in the banking system of the Persian Gulf Cooperation Council (GCC) and its economic effects, explored the factors associated with the creation of deferred receivables in the banking system of these countries. For this purpose, researchers studied two groups of explanatory variables, including macroeconomic variables and firm-level variables. The sample included a dynamic panel of data from 80 banks in the GCC region during 1995-2005 period. In order to estimate the studied models, different estimates of ordinary least squares, fixed effects, generalized differentia quadrature method and generalized systematic quadrature method were utilized. The estimation results indicate the effect of macroeconomic variables and banking variables on the formation of overdue receivables in GCC countries.

Louzis et al. (2011) in a study entitled "Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios " explored the determinants of overdue receivables. They used two groups of macroeconomic variables and banking variables in a dynamic data panel model to investigate the determinants of overdue receivables and credit risk in Greek banks. The sample in question was a balanced panel of data obtained from nine major Greek banks during 2003-2009, and the generalized quadrature method was utilized to estimate the model. The results showed that for various types of loans, outstanding claims in the Greek banking system were mainly affected by macroeconomic variables and management quality. However, the types of loans vary in the quantity of macroeconomic factors and the slightest reaction to changes in macroeconomic variables was related to mortgage loans. For various facilities, the GDP growth rate had a negative effect on the ratio of overdue receivables, and the unemployment rate wielded a negative effect on various loans, particularly in commercial loans.

Rathore and Mishra (2017) looked into the determinants of non-repayment of bank facilities among Indian farmers using the Logit and Probit model in a sample of 50 farmers. According to their results, low prices of agricultural products, high interest rates of bank facilities and low incomes of farmers are main factors that increase the probability of default on agricultural facilities.

Studies in Iran

Arab Mazar and Rouintan (2006) studied the determinants of credit risk in the Agricultural Bank’s credit records using the Logit method. Based on their results, the determinants of the probability of default were as follows: history of cooperation with the bank, history of overdue debt, loan sum, average balance of the account, debtor’s account turnover, creditor’s account turnover, current assets, creditors, bank debt, total debt, financial ratio.

The Studies and Marketing Department of Refah Bank (2007) conducted a study entitled "natural customer ranking of Refah Bank" using the AHP method to discover determinants of theprobability of loan default, which included manner of fulfilling obligations to the bank, the six-month average of account turnover in the bank, the type of collateral pledged, the sum of overdue debt, the length of the activity, the status of the business in terms of occupation, the total sum of debt to the bank, the number of cleared bounced checks, current bounced checks,

business experience, history of holding an account in the bank branch, good reputation, and six financial ratios including current ratio, quick ratio, sales return ratio, ownership ratio, debt ratio, special value ratio.
Mehrara et al. (2009) conducted a study entitled "Credit ranking of Parsian bank's legal clients using logit and Probit methods and artificial neural network". The results of this study, while lending credit to economic and financial theories, reflected that the performance of neural network model (percentage of its correct predictions) is considerably superior to conventional logit and probit econometric models. As for the determinants of credit risk, the findings showed that among the aforesaid variables, the type of collateral and liability ratio have the greatest effect on the probability of default. Also, the history of cooperation with the bank, current ratio, quick ratio and ownership ratio have anormal effect and other variables have a slight impact.
Shirinbakhsh, Yousefi and Ghorbanzad (2011) carried out a study entitled "Determinants of the probability of non-repayment of credit facilities. Case study: legal customers of the Export Development Bank of Iran)" using the logit method. According to the results, determinants of the credit risk of default probability were as follows: cash ratio to total liability ratio, asset turnover ratio, current ratio, cash ratio, free cash flow ratio, total liability ratio, current liability ratio to equity.
Mirzaei, Nazarian and Bagheri (2011) looked into the determinants of credit risk of legal entities in branches of Bank Melli in Tehran using the logit method. They found that the following factors had a bearing on the probability of default: type of business activity, type of contract, the sum of facility, type of facility, number of bank accounts, ratio of collateral to facility, history of cooperation with Bank Melli, previous debt to Bank Melli, quick ratio, total asset turnover ratio and ownership ratio.
Karimi et al. (2015) explored feterminants of credit risk of commercial bank customers in branches of Tejarat Bank in Mazandaran Province using the logit method. The results of this research illustrated that reducing the repayment period of the facility and increasing the facility rate augmented the probability of non-repayment. Also, in the case of various types of collateral, bank deposits and promissory notes had the highest and lowest impact on reducing the probability of non-repayment, respectively.
Ghasemi and Donyaei Harris (2016) measured customers' credit risk based on the neural network approach in one of the state banks. In this study, among 29 indicators extracted, 12 indices were identified based on experts' opinions: previous debt to the bank and bounced checks, customer account history, customer experience with the bank, asset turnover ratio, return on assets, return on equity, sales returns, debt ratio, leverage ratio, quick ratio, current ratio. Based on this, customer account history index and customer transaction history were identified as two main indicators.
Pourkazemi et al. (2017) conducted a study entitled "Estimating the probability of default in natural customers of banks using neural network method (Case study: Pasargad Bank)". The results of this study suggested that the neural network method can predict the probability of default in applicants with 92% accuracy. Regarding determinants of the probability of default, variables such as financial history and type of collateral wielded huge influence.
A review of domestic and international studies suggests that logit model is the model commonly adopted in the bulk of studies to explore the determinants of probability of default. Also, the artificial neural network has been primarily used for ranking. None of the Iranian studies have employed C-log-log model and the comparison of default probability estimation methods using logit and probit for banking facilities, especially the agricultural facilities granted by Bank Melli. Therefore, the main innovation of the present research is the adoption of the above model.

Research method (materials, methods, instrument, etc.)

In most of studies, econometric and neural network models as well as analytic hierarchy process have been used, and almost all studies have explored the determinants of the probability of default. In a 2006 study entitled "Predicting the probability of default in companies taking loan from German banks", Porath compared the three models of Logit, Probit and C-Log-Log in terms of determinants of the probability of default. Logit and probit are models commonly applied in this industry, but in theory, it seems that default behavior is more analogous to the C-log-log model. Therefore, based on this study, and drawing on previous research and available information, the present paper looks into the determinants of probability of default on agricultural facilities using Logit, Probit, and C-Log-Log models.
The study population consisted of medium and large companies in the agricultural sector that have received facilities from Bank Melli in KhorasanRazavi, North Khorasan and South Khorasan provinces during 2007-2017. Amongthese companies, 1395 were legal entities working in the agricultural sector of these three provinces, of which 286 companies were selected using simple random sampling method. The sample size (n=286) was taken from corporate files in these three provinces due to the availability of data. Large and medium-sized companies were chosen as the statistical population because they had audited financial statements. That is, the ratios and financial

ISSN- 2394-5125 VOL 8, ISSUE 02, 2021

information extracted from the financial statements are important and can impact the probability of default. Of these 286 companies, 150 (52.45% of companies) had a history of default and 136 (47.55%) had a clean record.
Equation (1) was used to estimate econometric models.

$$(1)\quad Y_n = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots \beta_n X_n + \varepsilon_n$$

In this equation, Y_n is the dependent variable and X_n represents independent variables of the research. Y_n denotestwo states of default and non-default. In fact, the dependent variable is equal to 0 in the case of default and 1 in the case of non-default.
Y = 0 non-defaulting
Y = 1 defaulting

X_1 to X_n are independent variables where X_1 is the fine amount; X_2 is facility repayment term, X_3 is the business history of the company, X_4 is the relevance of the CEO's education; X_5 is the experience of the CEO; X_6 is the total amount of indirect liabilities of the company to the banking system when receiving the facility; X_7 is the type of collateral pledged (immovable properties); X_8 is the type of collateral pledged (promissory note or check); X_9 is a single beneficiary company; X_{10} is the domestic production of raw materials; X_{11} is the branch's monitoring of how facilities are granted to the company; X_{12} is profits, X_{13} is the average amount of cash flow, and finally is X_{14} Altman Z-score (corporate financial strength).

β_1 to β_n are also model coefficients, indicating variation in the probability of default per unit change in X_1 to X_n variables. The study sample consisted of 286 companies, of which 136 (47.55%) belonged to Y=0 category (i.e. non-defaulting companies) and 150 (52.45%) to Y=1 category (i.e. defaulting companies).

Econometric models:
In order to study the determinants of the probability of default, the independent variables determined by the bank experts, as mentioned above, are factored into the Logit, Probit, and C-log-log models. Finally, independent variables that are significantly related to the dependent variable y (based on the final effect) and differentiate the two groups of creditworthy and non-creditworthy customers are selected. The probability of occurrence (P) of the event in question (here payment default) is assumed to be as follows:

(Whitehead, 2004): Whitehead j. (2004) An Introduction to Logistic Regression, Department of Economics, East Carolina University

$$(2)\ p_i = (y = 1) = \frac{1}{1+e^{-BX}} = \frac{e^{BX}}{1+e^{BX}}$$

In equation 1 we have:

$$(3)\ \frac{P}{1-P} = e^{B'X} = e^{B_0} + e^{B_1X_1 + \cdots . B_nX_n}$$

In the above relation, $\frac{P}{1-P}$ ratio indicates the probability of default. Considering the logarithm, we have:

$$(4)\ L = \ln\left(\frac{P}{1-P}\right) = \acute{B}X$$

In this regression, first the model (logit) is executed with independent variables and then the desirable independent variables are identified before developing the final model and estimating the model coefficients. Then, based on the final effects obtained, each customer's information is inputted to the model (logit) and the customer score (which is between 0 and 1) is determined. By comparing the customer score with the "acceptance threshold limit" or half (i.e. if the customer score is below 0.5, it is classified as low risk customers and if the score is higher than 0.5, it is classified as high risk customers), the bank decides whether to confirm or reject the borrower's application for taking banking facility.
In order to develop the validation model, all independent variables are entered into the logit model and in the fitted logit model, the significance of coefficients and the significance of the whole regression in the model are evaluated. Accordingly, independent variables that have significant final effects are identified as effective factors are utilized in the logit model to rank the recipients of facilities.

ISSN- 2394-5125 VOL 8, ISSUE 02, 2021

An appropriate cumulative distribution function (CDF) can be used to explain the behavior of a dependent variable divided into two groups. The estimated model, which is derived from the normal CDF, is generally known as the probit model and in some cases recognized as Normit model. In fact, it can be argued that for the above analysis, normal CDF can replace logistic CDF. Theoretically, logit and probit models are different in shape. The most notable difference is that the two ends of the logistic curve have a gentle slope, i.e. the normal curve approaches the axes faster than the logistic curve does (Trin, 2003). The CDF for the results of the standard normal distribution in the probit model is as follows:

$$(5)\ p_r(y=1|x)=\int_{-\infty}^{+\infty}\frac{1}{\sqrt{2\pi}}\exp\left(\frac{t^2}{2}\right)dt=\Phi(X\beta)$$

Other probability models can be constructed by selecting X_β functions ranging from 0 to 1. Another logistics model is the complementary log-log or C-log-log model, which was introduced by Agresti (1990):

$$(6)\ \ln(-\ln[1-p(y=1|x)])=X\beta$$

Or is equal to

$$(7)\ p_r(y=1\,|x)=1-\exp[-\exp(X\beta)]$$

Unlike the Logit and Probit models, the C-log-log model has an asymmetric distribution. In logit or probit models, when you are at a point on the probability curve where $p(y=1|x)=0.5$, increasing x by a value ofαwill augment the probability in the same way that decreasing xby a value of α would decreases probability. However, this is not the case with C-log-log models. First, in the probability function, with an increase in x, the probability surges slowly, and from a point on, the probability increase accelerates. Therefore, the asymmetric C-log-log model can also be used to identify determinants of the probability of default and rank recipients of facilities in the agricultural sector. Theoretically, it seems that the explanation of default behavior is closely associated with the C-log-log model. In a study on predicting the probability of default of companies in German banks, Porathcompared three models of logit and probit and C-log-log in terms of determinants of the probability of default. In this study, C-log-log models are used to test the research hypothesis.

Findings

In examining the details of the model, first the significance of all 14 variables was evaluated by z test statistics and the relevant probability. Variables that lacked sufficient evidence to support their significance were removed from the model. The remainder, which consists of 4 variables of the relevance of the CEO's education (X_4), a single beneficiary company (X_{10}), domestic production of raw materials (X_{14}), and Altman Z-scores (company's financial strength). The logit, probit, and C-log-log models were fitted with these four variables, respectively. In this model, the presented results suggested that all variables were significant at 95% significance interval. Therefore, the variables of the relevance of CEO's education, a single beneficiary company, the domestic production of raw materials and the company's financial strength had a bearing on the dependent variable. In the following, the research findings are presented for each model.

Given the logarithmic nature of logistic models, the coefficients could not be interpreted directly. Therefore, the solution for utilizing the final effect of variables was presented for this purpose. In other words, the effect of each variable on the probability of default on banking facilities is evaluated by estimating the final effect of those variables on the dependent variable, which are evaluated in comparison with the average values of independent variables.

Tables (1) to (3) show the mean values of each variable as well as the final effects of each variable at the mean point:

Table (1): The final effect of variables in the logit model

Variable	Coefficient (β) Final effects))	SD	z Value	Probability	Mean
Relevance of the CEO's education	0.22	0.13	1.66	0.098	0.35
A single beneficiary company	-0.22	0.13	-1.69	0.091	0.19
Domestic production of raw materials	0.20	0.10	1.82	0.069	0.49
company's	-1.14	0.21	-5.41	0.000	1.39

ISSN- 2394-5125 VOL 8, ISSUE 02, 2021

Financial strength

Source: Research Findings

Table (2): The final effect of variables in the probit model

Variable	Coefficient (β) Final effects))	SD	z Value	Probability	Mean
Relevance of the CEO's education	0.26	0.13	2.03	0.043	0.35
A single beneficiary company	-0.27	0.13	-1.99	0.046	0.19
Domestic production of raw materials	0.21	0.11	1.5	0.051	0.49
Company's Financial strength	-1.22	0.16	-7.80	0.000	1.39

Source: Research Findings

Table (3): The final effect of variables in the C-log-log model

Variable	Coefficient (β) Final effects))	SD	z Value	Probability	Mean
Relevance of the CEO's education	0.11	0.08	1.36	0.173	0.35
A single beneficiary company	-0.15	0.10	-1.53	0.127	0.19
Domestic production of raw materials	0.08	0.07	1.25	0.210	0.49
Company's Financial strength	-0.85	0.14	-5.89	0.000	1.39

Source: Research Findings

According to these tables, the final effects of variables are significant despite their small values. Before analyzing the findings, one of the models is selected according to the goodness of fit index (i.e. Log Likelihood in this research). This index was estimated to be -39.19 for the Logit model, -39.50 for the probit model, and -35.54 forin the C-log-log model, which shows a good fit of the probit model compared to the other two models. Therefore, research findings are analyzed according to the output of the probit model.

The results suggest that for one-unit increase in the relevance of the CEO's education, the facility's probability of default increases by 0.26%. Also, the facility's probability of default decreases by 0.27% with one-unit increase in the variable of a single beneficiary company and one-unit increase in the variable of domestic production of raw materials increases the facility's probability of default by 0.21%. Finally, highercompany's financial strength significantly lessens the risk of lending facility because one-unit increase in the company's financial strength lowers the probability of default by 1.22 percent. As can be seen, among 14 variables tested, these four variables have a significant relationship with the facility's probability of default.

Table (4): Actual and predicted values based on threshold level of 0.5 in the probit model

	Predicted values		
Actual values	0	1	Total observations
0	126	10	136
1	6	144	150
Total observations	132	154	186

Successful predictions:
Percentage of observations with a high probability of default that are correctly predicted = 96%
Percentage of observations with a low probability of default that are correctly predicted = 92.65%

ISSN- 2394-5125 VOL 8, ISSUE 02, 2021

Unsuccessful predictions:
Percentage of observations with high probability of default that are predicted with low probability of probability = 4%
Percentage of observations with low probability of default that are predicted with high probability of default = 7.35%

Source: Research Findings

As the results of Table (4) suggest, out of 150 observations with a high probability of default, 144 were accurately predicted, which accounts for 96% of the observations. Also, out of 136 observations with a low probability of default, 126 were accurately predicted, which makes up 92.65% of the observations. Moreover, out of 150 observations with high probability of default, 6 observations and out of 150 observations with low probability of default, 10 observations were not accurately predicted, which account for 4 and 7.35% of the observations, respectively. As can be seen, given the high predictive power of the model, the results are reliable.

Discussion

In this research, the determinants of probability of default on facilities granted by Bank Melli to the agricultural sector during 2007-2017 were studied and the estimated values of Logit, Probit, and C-log-log models were compared with each other. In these models, 14 variables including the fine amount, facility repayment period, company business precedent, relevance of the CEO's education, CEO's experience, the total amount of indirect liabilities of the company to the banking system when receiving the facility, the type of collateral pledged (immovable properties), type of collateral pledged (promissory note or check), a single beneficiary company, domestic production of raw materials, the branch's supervision over the use of facilities granted to the company, profits, average amount of cash flow and finally Altman Z-score (company's financial strength) were used. According to the results, only 4 variables of the relevance of the CEO's education, asingle beneficiary company, the domestic production of raw material and Altman Z score, or the company' financial strength index have significant effects on the probability of default. Among the models, the fitting power is higher in the Probit model than in the Logit and C-Log-log models. As the tables of actual values and predicted values depict, the probit model predicted and classified observations that had a high probability of default with 96% accuracy and observations with low probability of default with 92% accuracy. This manifests the reliability of the model. Also, as indicated by the table of final effects, the facility's probability of default is more sensitive to the company's financial strength so that with one-unit increase in the company's financial strength, the probability of facility's default decreases by 1.22 percent. Therefore, it is suggested that Bank Melli allocate more attention to the company's financial strength in order to reduce the risk associated with the granting of facilities.

References

Ghorbani, M., Nemati, A., &Ghorbani, R. . Investigating the willingness of wheat farmers to pay for weed control at different stages of its growth (Case study of KhorasanRazavi). Journal of Economics and Agricultural Development.2011. 25(1).

SharifiehRanani, H., Tavakoli A. &Honarvar, N. The effect of Agriculture Bank's credits on the value added of the agricultural sector in Iran. *Journal of Agricultural Economics and Development*. 2013. 21 (84): 205-227

Ronaghi, M., Bakhshudeh, M.. Investigating credits allocated to job creation and credit demand in agriculture of Fars province. *Economics and Agriculture*. 2014. 8 (1): 83-99

Bagheri, M., Najafi, B. Investigating the determinants of the repayment of agricultural credits (Case study: Fars province). *Iranian Journal of Economic Research*. 2004. 19 (3): 97-115

Bank Melli house organ No. 278 (https://www.bmi.ir/News/Journal/Details/46)

Bank Melli house organ No. 279 (https://www.bmi.ir/News/Journal/Details/51)

Brehanu, A. & B. Fufa. "Repayment Rate of Loans from Semi-Formal Financial Institutions Among Small- Scale Farmers in Ethiopia: Two – Limited Tobit Analysis", Journal of Socio – Economics. 2008. PP. 2221-2230

Adegbite, D. A. "Repayment Performance of Beneficiaries of Ogun State Agricultural and Multipurpose Credit", Agency (Osama) in Ogun state, Nigeria, American-Eurasian Journal of Sustainable Agriculture, 2009. Vol. 3, No. 1, PP. 117-125.

Acquah, H. D. & J. Addo. "Determinants of Loan Repayment Performance of Fishermen: Empirical Evidence from Ghana", CercetăriAgronomiceîn Moldova, XLIV. 2011. No. 4 (148).

Wongnaa, C. A. & D. Awonyu-Vitor. "Factors Affecting Loan Repayment Performance among Yam Farmers in the Sene District, Ghana", Agris Online Papers in Economics.2013. Vol. V, No. 2.

ISSN- 2394-5125 VOL 8, ISSUE 02, 2021

Sylvester, I., Okpara, G.C. & O. J.Chukwudi. "Determinants of Loan Size and Repayment Performance of Small Oil Producers in Nigeria: The Case Study of Abia State", International Journal of Business Management and Administration. 2013.Vol. 2, No. 3, PP. 043-054.

Espinoza, R. A., & Prasad, A. *Nonperforming loans in the GCC banking system and their macroeconomic effects*. International Monetary Fund. 2010. 14(3), 167-183

Louzis, D. P., Vouldis, A. T., & Metaxas, V. L. Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. *Journal of Banking & Finance*. 2012.*36*(4), 1012-1027

Kiran B. Analysis of loan disbursement to agricultural sector by Regional Rural Bank in Sirsa district of Haryana, India. International Research Journal of Social Sciences. 2015;4(3):54-7.

Rathore, R., Mishra, S., &Kumar, P. Factors affecting non-repayment of agricultural loan: a case Study of Rajasthan MarudharaGramin Bank, Agricultural Economics. 2017. *6*(4), 1052-1059

Arab Mazar, A., Ruyintan, P. Determinants of credit risk of bank customers: Case study: Agricultural Bank. *Journal of Economic Research*. 2006.3 (6): 45-80

Mehrara, M. Mosaei, M., Tasavori, M., Hassanzadeh, A. Credit ranking of Parsian Bank legal customers. *Journal of Economic Modeling*, 2009. 3 (4): 121-150

ShirinBakhshMasouleh, Sh., Yousefi, N., Ghorbanzad, J. Investigating the determinants of the probability of non-repayment of banks' facilities (Case study: legal customers of Export Development Bank of Iran). *Journal of Financial Analysis of Securities Analysis*, 2011.4 (12): 111-137

Mirzaei, H., Nazaria, R., and Bagheri R. Study of determinant of credit risk of legal customers of banks (Case study: Bank Melli branches, Tehran).".2011. 67-98.

KarimiMoghari, AsadiGorji, H. GilakHakimabadi, M.T. Determinants of credit risk of commercial banks' customers (Case study: Tejarat Bank, Neka City, Mazandaran Province). *Monetary Economics*. 2015. 22 (10), 206.

Ghasemi A.R., &Donyaee Harris, T. Measuring customers' credit risk through a neural network approach in one of the state banks. *Financial Engineering and Securities Management* (portfolio management) . 2016. 7 (27). 155-181.

Pourkazemi, M.H., Sedaghatparast, A., &Dehpanah. Estimating the probability of default for the bank's natural customers using neural network method (Case study: Pasargad Bank). *Journal of Islamic Financial Studies and Banking*. 2017.3 (Autumn and Winter), 1-23.

Porath, D. Estimating probabilities of default for German savings banks and credit cooperatives. *Schmalenbach Business Review*. 2006.*58*(3), 214-233.

Whitehead D, Beadle CL. Physiological regulation of productivity and water use in Eucalyptus: a review. Forest ecology and management. 2004 May 17;193(1-2):113-40.

Train, K., &Sonnier, G. Mixed logit with bounded distributions of partworths. *Applications of Simulation Methods in Environmental Resource Economics, edited by A. Alberini and R. Scarpa. New York: Kluwer Academic*. 2003.

Agresti A, Mehta CR, Patel NR. Exact inference for contingency tables with ordered categories. Journal of the American Statistical Association. 1990 Jun 1;85(410):453-8.

Economic indicators of the Central Bank of Iran https://www.cbi.ir