Predicting the Default Characteristics of Microfinance Borrowers in Turkey: A Probit Analysis

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Abstract
This article is the first complete study that identifies the common idiosyncratic characteristics of defaulted microfinance loans in Turkey by using a probit analysis. The study is based on 104,393 observations from a pooled data that was provided by the Turkish Grameen Microfinance Program (TGMP). Three models were designed and two tests were used in attempting to find the appropriate decision model to identify default. According to the hypothesis test results of the most appropriate model, seventeen variables were highly significant at the one percent level. This probit model may be used by Turkish microfinance institutions as a criterion to identify the likeliness of potential borrowers' repayments.

Key Words: Probit Analysis, Decision Model, Loan Defaults, Microfinance Repayment, Econometrics

1. Introduction

Millions of people around the globe are aware of the unfortunate facts of unsolvable poverty and its consequences. Governments, non-profit organizations, corporations and others have spent trillions of dollars to fight poverty, but still eighty percent of humanity lives under $10 a day (Ravallion et al. 2008). Many experiments and studies have been executed in order to find ways to make development policies more efficient – to decrease inequality, poverty, and to achieve the United Nations Millennium Development Goals(Littlefield et al. 2003; Yunus 2003, 2004). Unfortunately, even now, no one has found a solution that will eliminate poverty. While this does not imply that donor aid, as it exists today, does not work, the persistence of poverty calls into question the amount of money spent on traditional development programs (Karlan and Appel 2011).

Microfinance has been on the market for decades, providing loans to individuals that were neglected by traditional financial intermediaries. This financial innovation brought about positive changes to millions of lives (Durrani et al. 2011). The history of microfinance starts in the eighteenth century. Jonathan Swift, an Irish author and politician, inspired one of the very first microfinance organizations, the Irish Loan Funds system that reached its peak loan coverage of twenty percent of Irish families during the 18th century (CGAP 2006). Microfinance innovation has become a popular development instrument that has been adopted by many nations. Yunus entered the microfinance business when he lent his initial $27 to 42 bamboo craftswomen (Yunus 2004). This successful venture encouraged him to continue his microfinance journey that eventually designated him as being the father of microfinance as well as being the founder of Grameen Bank, a non-profit organization that serves over six million clients with a loan portfolio of $650 million (Karlan and Appel 2011). This won for him and his organization the honor of becoming the 2006 Nobel Peace Laureate (Hesser 2006; Friedman and Aziz, 2012).

Today, over 155 million low-income individuals, mostly women (Adebayo 1997; Adeyeye 2003; Morvant-Roux et al. 2012) are part of the microfinance family (Leatherman and Dunford 2010; Buera, Kaboski and Shin 2012). Based on the stories of microfinance clients, microfinance has made dreams happen and changed lives (Khandker 2005; Aziz et al. 2013). Still, this is neither an indicator that microfinance has been used at its most efficient capacity, nor does it indicate that microfinance has increased all of its clients' standards of living (Westover 2008). Some tests in South Africa and the Philippines and a recent study that was conducted in Bosnia and Herzegovina by Britta Augsburg et al. (2012), are used to identify the impacts in different ways of the microfinance clients' lives and the success of repayments based upon different requirements.

Nonetheless, there are not many studies that analyze the characteristics of microfinance loan defaults and no study that particularly focuses on Turkey in terms of microfinance defaults. As previously mentioned, in order to maximize the effect of microfinance on reducing poverty, it is necessary to analyze the idiosyncratic reasons of common default characteristics. By doing so, managers of microfinance institutions (MFIs) in Turkey can reduce the prevalence of bad loans and find ways to guide microfinance clients to overcome these problems (Yildirim 2008). This study uses a probit analysis to identify the common default characteristics of 104,393 observations conducted by the Turkish Grameen Microfinance Program (TGMP).

Among the recent publications and studies on microfinance, relatively few researchers used a probit analysis in their studies, and just a couple of these researches specifically focused on the characteristics of microfinance defaults by using a probit analysis. Chirwa used a probit analysis on a dataset conducted in Malawi to determine the probability of credit repayments over ten years ago (1997). However, Chirwa used a stepwise elimination to identify the model's specification of the X-vector (Adeyemo 2007). Stepwise elimination is highly criticized and considered unethical because of the lack of theoretical input and the possibility of biasness and inconsistence when relevant variables were excluded (Cohen and Cohen 2003). Adeyemo et al. used linear multiple regression analysis on a relatively small sample (i.e., n=200) to determine the factors that affected microfinance repayments (2007). Vitor et al. used a probit analysis to determine loan repayment defaults among farmers in Ghana based on a relatively small sample (i.e., n=374) (2012). In this article, it is unclear how the small dataset was collected. Therefore, there is a high possibility of selection bias if the clients were not randomly selected (Cortes et al. 2008).

This study will demonstrate an appropriate (and recent) model that may be used by microfinance institutions in Turkey in order to find the likeliness of a default. Since the suggested model is based on a study of 104,393 observations, in the probability theory the law of large numbers guarantees that the estimated parameters are converged with the actual parameters as the sample size rises (Hsu and Robbins 1947). Thus, this model can precisely measure the probability that the borrowers in the sample, given a host of characteristics based on available data, defaulted or not on their loans.

2. The Model

In this paper, a probit analysis is applied to a binary choice model to identify the characteristics of microfinance borrower who continuously could not finance their loans.

TGMP has tried to secure itself by not allowing defaults. However, since there are no regulatory protections and screening mechanisms (e.g., credit bureaus), it can be more expensive for the microfinance organization to overcome such asymmetric information problems (Pham et al. 2008). In order to be more cost efficient and achieve the purpose of microfinance, while also keeping in mind the best interests of low-income individuals, MFIs must lower these opportunity losses. Throughout this paper, borrowers who could not refinance their loans within 46 weeks are considered as defaulters.

In the models it is assumed that the error terms are homoscedastic and normally distributed with a mean of zero, and a variance of σ^2. Since one variable contains a large amount of incorrect information, there are three models constructed in order to test which model is more appropriate by using one t-test and one likelihood-ratio test. For all models, the dependent variable is the qualitative variable, Defaulted, which means a borrower has not been able to pay back her loan within 46 week maturity deadline. This dependent dummy variable may be represented as follows:

$$Select\ Y_i = 1 <=> Z_i \geq 0$$
$$Select\ Y_i = 0\ <=> Z_i < 0$$

For model I, the probability of choosing $Y_i = 1$ (i.e., default is present) is given by: $Prob(Y_i = 1) = Prob(Z_i \geq 0) = Prob(\beta_0 + \beta_1\ balance\_on\_savings + \beta_2\ Mediterr + \beta_3\ Southeast + \beta_4 Aegean + \beta_5 Marmara + \beta_6 Central + \beta_7 Black\_Sea + \beta_8 Age + \beta_9 passive + \beta_{10}\ years\_active\_passive + \beta_{11} ag + \beta_{12} loannumber + \beta_{13} insurance\_1 + \beta_{14} total\_loan\_amount + \beta_{15} outstanding\_loan + \beta_{16} married + \beta_{17}\ widowed\_separated\_divorced + \beta_{18} household\_size + \beta_{19}\ established\_business - u_i \geq 0)$ **(1)**

$$= Prob(\ \beta_0 + \beta_1 Balance\_on\_savings + \cdots + \beta_{19}\ established\_business \geq u_i)$$
$$= Prob(\ [\beta_0 + \beta_1\ Balance\_on\_savings + \cdots + \beta_{19}\ established\_business]/\sigma \geq [u_i/\sigma]).$$

To simplify the calculation let $Z_i^* = [\beta_0 + \beta_1\ Balance\_on\_savings + \cdots + \beta_{19}\ established\_business]/\ \sigma$. Using this new definition: $Prob(Y_i = 1) = Prob\left(\frac{u_i}{\sigma} \leq Zi^*\right) = \phi\ Zi^*$, where ϕ stands for the cumulative probability function for a standard normal variate, the first probit model is given by:

$$Prob(\text{Defaulted} = 1) = \phi\ (\beta_0 + \beta_1 Balance\_on\_savings + \cdots + \beta_{19}\ established\_business). \quad \textbf{(2)}$$

For model II, the variable "years_active_passive" was excluded because it contained 13,590 observations with errors, which is not having an exit date entered into the system. The probability of $Prob(Y_i = 1) = Prob(Z_i \geq 0)$ choosing $Y_i = 1$ (i.e., default is present) for the second model is given by: $Prob(\beta_0 + \beta_1\ balance\_on\_savings + \beta_2\ Mediterr + \beta_3\ Southeast + \beta_4\ Aegean + \beta_5\ Marmara + \beta_6\ Central + \beta_7 Black\_Sea + \beta_8\ Age + \beta_9 passive + \beta_{10} ag + \beta_{11} loannumber + \beta_{12} insurance\_1 + \beta_{13} total\_loan\_amount + \beta_{14} outstanding\_loan + \beta_{15}\ married + \beta_{16}\ widowed\_separated\_divorced + \beta_{17} household\_size + \beta_{18} established\_business - u_i \geq 0)$ **(3)**

$$= Prob(\beta_0 + \beta_1 Balance\_on\_savings + \cdots + \beta_{18}\ established\_business \geq u_i)$$
$$= Prob(\ [\beta_0 + \beta_1\ Balance\_on\_savings + \cdots + \beta_{18}\ established\_business]/\sigma \geq [u_i/\sigma])$$

To simplify the derivation let $Z_i^*= [\beta_0 + \beta_1\ Balance\_on\_savings + \cdots + \beta_{18}\ established\_business]/\sigma$. Using this new definition: $Prob(Y_i = 1) = Prob\left(\frac{u_i}{\sigma} \le Zi^*\right) = \phi\ Zi^*$, the second probit model is given by:
$Prob(\text{Defaulted} = 1) =$
$\phi\ (\beta_0 + \beta_1 Balance\_on\_savings + \cdots + \beta_{18}\ established\_business)$. **(4)**

For model III, the insignificant variables: balance on savings, agriculture, and outstanding loan, at significance levels one percent, five percent, and ten percent, were excluded because they produced insignificant estimators based on models I and II. The probability of choosing $Y_i = 1$ for the third model is given by:

$Prob(Y_i = 1) = Prob(Z_i \ge 0)$ =Prob(β_0 + β_1 Mediterr + β_2 Southeast + β_3 Aegean + β_4 Marmara+ β_5 Central + β_6Black_Sea + β_7 Age+ $\beta_8$passive + $\beta_9$loannumber + β_{10}insurance_1 + β_{11}total_loan_amount + β_{12}married + β_{13} widowed_separated_divorced + β_{14}household_size + β_{15}established_business- $u_i \ge 0$) **(5)**
$= Prob(\beta_0 + \beta_1 \text{Mediterr} + \cdots + \beta_{15}\ established\_business \ge u_i)$
$= Prob(\ [\beta_0 + \beta_1 \text{Mediterr} + \cdots + \beta_{15}\ established\_business]/\sigma \ge [u_i/\sigma]$.
To simplify the derivation let $Z_i^*=[\beta_0 + \beta_1 \text{Mediterr} + \cdots + \beta_{15}\ established\_business]/\sigma$. Using this new definition: $Prob(Y_i = 1) = Prob\left(\frac{u_i}{\sigma} \le Zi^*\right) = \phi\ Zi^*$, the second probit model is given by:
$Prob(\text{Defaulted} = 1) = \phi\ (\beta_0 + \beta_1 \text{Mediterr} + \cdots + \beta_{15}\ established\_business)$, **(6)**
in which ϕ stands for the cumulative probability function for a standard normal variate.

3. Data

The empirical results provided below are estimated based on 104,393 microfinance clients' observations, as of November 2012. This pooled data was provided by TGMP's database, known as "Damlabank." The variables that are used to explain the default characteristic include Turkey's seven regions, whether or not the client has established a business, the number of loans a client has taken, whether the client is married, single or widowed, and seven other variables. A more detailed description of these variables is available in Table 1.1. , Tables 1.2, which are below, provide information about the summary statistics of the data set. All of the 15 dummy variables had a minimum of zero and a maximum of one. As it appears on Table 1.4, the statistics program excluded 16,975 observations because of missing information and possible human error. In models I and III, 15,422 observations were extracted; however, when the variable "years_ __passive," was excluded in model II, only 3,382 observations were missing. In the Empirical Result section, one t-test and one likelihood-ratio test are used to determine which model is more appropriate to use as a model to test for microfinance defaults.

Table 1.1 - Variable definitions (alphabetically)	
Aegean	1 if borrower is from Aegean region (=0 otherwise)
Ag	1 if borrower has used the loan for agriculture purpose (=0 otherwise)
Age	Age of the borrower
Balance_on_savings	Total deposits minus total withdrawals
Black_Sea	1 if borrower is from Black Sea region (=0 otherwise)
Central	1 if borrower is from Central region (=0 otherwise)
East	1 if borrower is from East region (=0 otherwise)
Established_business	1 if borrower had established a small business before taking a loan (=0 otherwise)
Household_size	Household size of the borrower
Insurance_1	1 if borrower has a micro-insurance account (=0 otherwise)
Loannumber	Number of separate loans the borrower has received
Marmara	1 if borrower is from Marmara region (=0 otherwise)
Married	1 if borrower is married (=0 otherwise)
Mediterr	1 if borrower is from Mediterranean region (=0 otherwise)
Outstanding_loan	Amount of money a borrower owes TGMP
Passive	1 if borrower has stopped taking loans from the organization (=0 otherwise)
Defaulted	1 if borrower cannot pay its loan back (=0 otherwise)
Single	1 if borrower has never been married (=0 otherwise)
Southeast	1 if borrower is from Southeast region (=0 otherwise)
Total_loan_amount	Cumulative amount of loans borrower has received from TGMP
Widowed_separeted_divorced	1 if borrower had previous marriage (=0 otherwise)
Years_active_passive	How long the borrower has been involved in TGMP

Table 1.2 - Summary Statistics (n=104,393)

Variables	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*
balance_on_savings	84.729	815.832	0	18598
Mediterr	0.151	0.358	0	1
Southeast	0.352	0.478	0	1
Aegean	0.092	0.289	0	1
Marmara	0.100	0.300	0	1
Central	0.136	0.343	0	5
Black_Sea	0.093	0.290	0	1
East	0.076	0.265	0	1
Age	38.919	12.189	0	95
passive	0.426	0.494	0	1
years_active__passive_	1.556	1.280	0	9.667
ag	0.055	0.229	0	1
loannumber	2.690	1.591	1	17
insurance_1	0.230	0.421	0	1
total_loan_amount	1873.780	1447.8	0	2.45E+04
outstanding_loan	351.648	741.434	0	18598
married	0.829	0.377	0	1
single	0.111	0.314	0	1
widowed_separated_divorced	0.057	0.231	0	1
household_size	4.191	1.739	1	20

defaulted	0.029	0.167	0	1
established_business	0.007	0.085	0	1

4. Empirical Results

4.1. Model I:

The empirical results from the probit analysis for model I is presented in Table 1.3 below. Maximum likelihood estimators are consistent, efficient, and provide asymptotically correct t-ratios (White 1982). It is important to remember if a coefficient has a positive sign and is statistically significant, an increase in that variable will increase the probability (at a diminishing rate) of incurring a default.

17 variables are significant at the one percent level because the p-values are smaller than one percent for all except for the variables balance on savings, agriculture, and outstanding loan. A third model was designed in order to investigate if there is an improvement when the insignificant variables: balance on savings, agriculture, and outstanding loan, are excluded. Model III will be compared with model I in the likelihood ratio test section. The estimated coefficients are present on Table 1.3.

In interpreting these estimations, it is interesting to notice that the probability of default increases when the microfinance borrower is located in the central region, has been involved in the organization for a longer period of time, uses her loan for an agriculture-related business, has taken larger numbers of loans, is widowed (or separated or divorced), had established a business before taking the loan, and is passive. Likewise, if a borrower is located in the other regions that are included in the model, is older, has received a large cumulative amount of loans from TGMP, owes a larger amount of money to TGMP, is married, and has a larger household size, they are more likely to pay back the loan.

Table 1.3 - Model 1

Variables	***Coefficient***	***Std. Error***	***z***	***p-value***
const	-2.634***	0.0703	-37.487	1.49E-307
Age	-0.005***	0.0009	-5.490	4.03E-08
passive	0.218***	0.0288	7.594	3.09E-14
years_active_passive	0.136***	0.0082	16.569	1.17E-61
ag	0.0480	0.0497	0.972	0.331
loannumber	0.685***	0.0186	36.853	2.58E-297
insurance_1	-0.362***	0.0900	-4.025	5.69E-05
total_loan_amount	-0.001***	0.0000	-32.581	7.72E-233
outstanding_loan	-0.00001	0.0000	-0.763	0.446
married	-0.102***	0.0338	-3.030	0.002
widowed_separated_divorced	0.137***	0.0523	2.623	0.009
household_size	-0.029***	0.0066	-4.523	6.10E-06
established_business	0.419***	0.1073	3.908	9.30E-05
balance_on_savings	0.000002	0.0000	0.102	0.919
Mediterr	-1.516***	0.0827	-18.341	3.93E-75
Southeast	-0.571***	0.0385	-14.830	9.40E-50
Aegean	-0.364***	0.0498	-7.300	2.88E-13
Marmara	-1.126***	0.0822	-13.693	1.12E-42
Central	0.173***	0.0393	4.398	1.09E-05
Black_Sea	-0.261***	0.0435	-6.006	1.90E-09

*Significant at the 10% level ** Significant at the 5% level *** Significant at the 1% level
Log-likelihood -7959.517; Likelihood ratio test: Chi-square(19) = 4754.38 [0.0000]

4.2 Model II:

The empirical results for the second model are in Table 1.4. The same assumptions for the maximum likelihood estimators are valid for the second model as well. By looking at the p-values of the estimators, all estimators except the balance on savings variable are significant at the five percent level, and 15 estimators are significant at the one percent level. Only the sign of the variable, "balance on savings," has changed. The other estimators' sign stayed constant, but the coefficients changed slightly. Let's examine if there is a large difference by excluding the variable, "years_active_years." The estimated coefficients of the second model are present in Table 1.4, which can be found below.

Table 1.4 - Model 2

Variables	***Coefficient***	***Std. Error***	***z***	***p-value***
const	-2.763***	0.0653	-42.323	0
Age	-0.004***	0.0008	-5.1235	3.00E-07
passive	0.072***	0.0255	2.8202	0.0048
ag	0.094**	0.0450	2.091	0.03652
loannumber	0.789***	0.0177	44.4851	0
insurance_1	-0.407***	0.0883	-4.6101	4.02E-06
total_loan_amount	-0.001***	1.65E-05	-35.4691	1.47E-275
outstanding_loan	-0.00005**	2.49E-05	-2.0292	0.04243
married	-0.068**	0.0316	-2.154	0.03124
widowed_separated_divorced	0.165***	0.0485	3.4035	0.00067
household_size	-0.023***	0.0061	-3.8231	0.00013
established_business	0.296***	0.0944	3.1341	0.00172
balance_on_savings	0.00001	1.79E-05	0.4978	0.61862
Mediterr	-1.401***	0.0752	-18.6228	2.10E-77
Southeast	-0.440***	0.0354	-12.4307	1.78E-35
Aegean	-0.317***	0.0451	-7.0287	2.09E-12
Marmara	-1.076***	0.0801	-13.4326	3.90E-41
Central	0.248***	0.0359	6.8897	5.59E-12
Black_Sea	-0.244***	0.0414	-5.9014	3.60E-09
*Significant at the 10% level ** Significant at the 5% level *** Significant at the 1% level				
Log-likelihood -9236.63; Likelihood ratio test: Chi-square(18) = 5352.31 [0.0000]				
Excluded the variable, "years_active_passive"				

4.3. T-Test:

The t-test below determines whether or not including the variable "years_active_passive" makes a difference in the models at a five percent significance level. The null hypothesis is that the coefficient of the variable, "years_active_passive," equals zero (i.e., H_0: $\beta_{19} = 0$). The alternative hypothesis is that the coefficient of the variable, "years_active_passive." does not equal zero (i.e., H_1: $\beta_{19} \neq 0$). The estimated t-statistics equals: $t = \hat{\beta}_{19} \,/\, \hat{\sigma}_{19} \; = \; 0.136/0.008 = 17.$

Since there were a total of 88,960 observations and 20 variables, the critical values at a significance level of five percent equals -1.959 and 1.959. The null hypothesis will be rejected if the estimated t-ratio is either greater than 1.959 or less than -1.959. There is enough evidence to reject the null hypothesis at a five percent significance level. Thus, model I is more appropriate compared to model II to measure the default rates, even though there is a large amount of lost observations.

4.4. Model III:

Model III is designed in order to test whether excluding the insignificant estimators, balance on savings, agriculture, and outstanding loan, at significance levels one percent, five percent, and ten percent, from model I can improve the model to test the likeliness of defaults. As aforementioned, the same assumptions for the maximum likelihood estimators are valid for this model. The empirical results of the estimations from the probit analysis can be viewed in Table 1.5.

An increase in the coefficients Mediterr, Southeast, Aegean, Marmara, Black_Sea, Age, insurance_1, total_loan_amount, married, and household_size, decreases the probability of a microfinance default. As a microfinance client's age increases, the probability of a default decreases. It is interesting to note that when the client receives a higher cumulative amount of loans and has a larger family, it is more likely that the client will refinance her loan.

Similarly, the coefficients Central, passive, loannumber, widowed_separated_divorced, established_business, and years_active_passive designate that an increase in these variables increases the probability of a default. It is remarkable that when a client is involved in the organization for a longer time and has established a business prior to her loan, they are likely to have a default, *ceteris paribus*. A client who had established a business prior to taking a loan, may use her business as collateral, and may be able to receive a loan from another financial intermediary. If such a client is applying for a loan from a MFI, it may be because they already have a debt, and could not finance it.

Table 1.5 - Model 3

Variables	***Coefficient***	***Std. Error***	***z***	***p-value***
const	-2.643***	0.070	-38.015	0
Age	-0.005***	0.001	-5.459	4.78E-08
passive	0.224***	0.028	8.129	4.32E-16
loannumber	0.686***	0.018	37.174	1.83E-302
insurance_1	-0.363***	0.090	-4.034	5.47E-05
total_loan_amount	-0.001***	0.000	-34.360	9.97E-259
married	-0.103***	0.034	-3.042	0.002
widowed_separated_divorced	0.137***	0.052	2.621	0.009
household_size	-0.029***	0.007	-4.440	9.00E-06
established_business	0.427***	0.107	3.995	0.0001
Mediterr	-1.514***	0.083	-18.305	7.49E-75
Southeast	-0.569***	0.038	-14.789	1.73E-49
Aegean	-0.363***	0.050	-7.285	3.22E-13
Marmara	-1.126***	0.082	-13.701	9.97E-43
Central	0.174***	0.039	4.422	9.78E-06
Black_Sea	-0.260***	0.043	-5.986	2.14E-09
years_active_passive	0.137***	0.008	16.815	1.89E-63

*Significant at the 10% level ** Significant at the 5% level*** Significant at the 1% level

Log-likelihood -7966.522; Likelihood ratio test: Chi-square(16) = 4757.06 [0.0000]

Excluded variables "balance on savings", "agriculture", and "outstanding loan."

Furthermore, from a theoretical perspective, the variables “balance on savings", "agriculture", and "outstanding loan” are irrelevant. First, as it can be viewed on Table 1.2 the average balance on savings is about 85 Turkish Liras, which is equivalent to \$38.7.[1] This is a relatively small amount compared to loan amounts that clients received. Second, about 5.5% of all clients have used loans for agricultural purposes. Since this number is relatively small, this variable is irrelevant to explain loan defaults. Third, the variable outstanding loan is almost the same as the total loan amount. Therefore, omitting this variable from the default model would be appropriate. All the other variables were from a theoretical perspective important to explain defaults. In fact, excluding relevant variables from the model would create more serious problems than including irrelevant variables. Thus, in Model 3 I have included all variables that were statistically and theoretically important to explain defaults.

4.5. Likelihood Ratio Test:

The likelihood ratio test below demonstrates whether excluding the insignificant variables from model I improved model III. The variables, balance of savings, agriculture, and balance of the outstanding loan, were excluded in model III. The null hypothesis is that the coefficients of the variables, balance of savings, agriculture, and balance of the outstanding loan [from equation two], equal zero (i.e., H_0: $\beta_1 = \beta_{11} = \beta_{15} = 0$). The alternative hypothesis is that at least one of the coefficients of the variables, balance of savings, agriculture, and balance of the outstanding loan~~,~~ do not equal zero (i.e., H_1: *At least one of* $\beta_1, \beta_{11}, \beta_{15}$ *is not equal to zero*). A Likelihood Ratio tests whether the null hypothesis can be rejected, or fail to be rejected, at the five percent significance level:

$$ln(L_R) = -7,966.522 \; ln(L_U) = -7,959.517$$

Likelihood statistics$= -2\ (ln(L_R) - ln(L_U) = -2\ (-7966.522\ -\ (-7959.517))\ =$ $14.01.$

The likelihood ratio statistics follows a chi-square distribution with *m* degrees of freedom (i.e., $\chi^2(m)$), where *m* is the number of restrictions imposed in the null hypothesis. Likelihood Ratio Statistics=$\chi^2(3) = 7.815.$

The null hypothesis can be rejected if and only if the likelihood statistics is greater than the likelihood ratio statistics. Therefore, there is evidence that null hypothesis will fail to be rejected at a five percent significance level. Thus, the model III is more appropriate compared to model I to measure the default rates.

5. Conclusion

Based on the three models, the t-test, and the Likelihood Ratio Test, the best model that may be used as criteria and guidance to identify the probability of microfinance loan defaults is model III. This model says that if a client is from the Central region; is passive; has taken a higher number of loans; is widowed, separated, or divorced; has established a business prior taking a loan; or is longer involved in the organization, there is an increase in the probability of a default.

[1] The closing exchange rate of September 9th, 2014 was 2.196 TRY for 1 USD.

In order to understand better why the six variables increased the probability of default, a field study was conducted in Turkey for three months from May 2013 to August 2013. Over sixty microfinance clients who have either a potential to be defaulters or are already defaulters were visited. Also, over ten employees at TGMP who were working closely with clients were interviewed. These employees were asked why there was an increase in the probability of default when the six positively signed variables from model three were present.

In the central region, there was a high population of Romani people. According to the regional director and branch manager, the main factor of high defaults in the central region was because of the high population of Romani people not repaying their loans and seasonally leaving the cities where they have taken the microfinance. Therefore, the employees at TGMP were not able to get in contact with some clients in the central region. For example, Eskisehir, a city in the central region, had a default population of over 22%. In this case, according to the regional and branch managers, the seasonal migration of the Romani people was the chief reason for default. This could explain why the regional dummy variable has a positive impact on the probability of default.

Let’s look at the reasons of increase in probability of default from the presence of variables two and three. Clients who wanted to take a larger loan had to wait until they repaid their first loan of 1,000 Turkish Lira. This is a policy of TGMP to establish trust between its clients and the organization. After their first loans, clients had the opportunity to take larger loans. Based on the interviews, clients who have taken a higher number of loans were not able to repay their loans because they had to pay much more on weekly basis than they could earn. Also, it is important to notice that clients who have taken a larger loan were automatically longer involved in the organization. This explains why the clients who have taken larger loans and have been longer involved in the organization were not able to repay their loans.

TGMP employees preferred to give additional loans to members who have been able to repay their loans on time and were not defaulted. Therefore, clients who were passive (i.e., borrower has stopped taking loans from the organization) were not able to receive a new loan either because clients have understood that they could not repay another loan or they were not eligible to receive a new loan because of their defaults. This explains the fourth variable- passive borrowers.

Interestingly, husbands had a key role in loan repayments. Clients who were married and who were interview said that their husbands helped them to pay their weekly repayments. Some clients who were widowed, separated, or divorced had received previous help from their husbands, but when the husband divorced or separated from the client, then she had a difficult time to repay her loans. This illustrates the reason of the increase in probability of default when the variable -widowed, separated, or divorced- is present.

TGMP’s regional managers and branch managers have confirmed that many defaulted clients who had established a business prior to taking a loan either to repay another loan from a commercial bank or the client did not know how to run a business efficiently. Or according to Karlan and Appel (2011) having the business is the only choice that the client has to survive. To solve this problem, MFIs may cooperate with other non-profit or government agencies to find better business opportunities for a client who has established a business and was not successful in operating her business or MFIs may provide training on how to run a business which may improve repayment (Karlan and Valdivia 2011; Karnani 2007). This illustrates how MFIs may handle the presence of the sixth variable.

Microfinance organizations that offer loans only to women and are located in Turkey may use this model to test whether a specific client can repay her loan based on the 16 characteristics that are included in the equation. Also, these organizations may use this model as a rule to realize that the six variables - central region; is passive; has taken a higher number of loans; is widowed, separated, or divorced; has established a business prior taking a loan; or is longer involved in the organization - are correlated with an increased probability of a default, *ceteris paribus*. Since the estimations are significant at one percent, five percent, and ten percent levels, it is a good common measurement to estimate whether clients can repay their loans (Murphy et al. 2009).

The recent financial crisis has shown that even well educated people in more-developed nations fail to make the best choices (Karnani 2007; Karlan and Appel 2011). In order to make microloans more successful, MFIs have to ensure that more is done than just good intentions (Karlan and Appel 2011). Without doubt, most organizations that serve the poor have the mission to help individuals who are not as fortunate as wealthier people. Microfinance is a powerful tool to decrease poverty. Many studies have shown that microfinance has been able to decrease poverty in many regions (Latifee 2003; Chowdhury et al. 2005; Coleman 2006). However, MFIs have to ensure that the microloans will have a relatively low potential to default (Jain and Mansuri 2003).

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