DETERMINANTS OF LOAN REPAYMENT PERFORMANCE IN ACSI

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Abstract: *The main problem of the poor performance of financial institutions in many developing countries is high rate of non-repayment of loan (Fikirte, 2011). This study was intended to identify the determinants of loan repayment performance of ACSI. Hence, depending on theoretical, empirical works and institution specific contexts, the study incorporated different variables which simultaneously affect loan repayment performance of clients of ACSI. On the other hand, in order to identify the factors affecting loan repayment performance descriptive statistics and multinomial logit model were employed. Accordingly, out of fourteen variables hypothesised to affect loan repayment performance of borrowers, eight variables were found to be statistically significant. The maximum likelihood estimates of multinomial logit model showed that sex, age, education level, loan size, interest rate, loan tenure, training and monthly sale were factors affecting loan repayment performance of borrowers of ACSI.*

Key words: *ACSI, loan repayment performance, loan paid on time, delinquents, defaulters, Multinomial logistic regression*

1. INTRODUCTION

In many developing countries, poverty has become sever leaving millions of people out of basic needs for survival (Fikirte, 2011). To relieve financial constraints and alleviate poverty, MFIs provides financial services to the poor (Godquin, 2004; Fikirte, 2011). In addition, the availability of financial services plays an important role in improving economic and social status of the poor (Fikirte, 2011; Mokhtar et al., 2012). On the other hand, financial sustainability of MFIs is a prerequisite for making microfinancial services permanent as well as widely available (Million et al., 2012; Nawai and Shariff, 2012). In these regard, the main problem of poor performance of MFIs is high rate of non-repayment of loans (Fikirte, 2011; Mokhtar et al., 2012; Million et al., 2012).

For instance, improving repayment performance might help MFIs to reduce dependency on subsidies (Godquin, 2004; Fikirte, 2011) by operating on sustainable basis (Nawai and

Shariff, 2012). Furthermore, high repayment rate enables the borrowers to obtain higher amount of next loan (Fikirte, 2011) and also enables MFIs to cut the interest rate it charges thereby allowing more borrowers to have access to credit (Godquin, 2004). In general, good repayment performance is an indicator of effective MFIs.

In contrast, the numbers of defaulters have been challenging MFI's objectives by retaining large amount of loan (Pasha and Tolosa, 2014). Consequently, the problem leads to system failure to implement appropriate lending strategies and policies (Million et al., 2012; Zelalem et al., 2013). In addition, low repayment rate discourages MFIs from refinancing the defaulting members (Fikirte, 2011; Million et al., 2012; Zelalem et al., 2013). After all, the repayment problem hinders efforts to combat poverty and realization of sustainability of MFIs (Pasha and Tolosa, 2014).

Therefore, this study was undertaken to analyses how the loan repayment performance of defaulters, delinquents and clients with loan paid on time were associated with different institutional as well as demographic and socio economic characteristics.

The remainder of the paper is organized into four sections. Section two examines methods of estimation such as descriptive statistics and multinomial logit model whilst section two examines about description of variables which were used in the descriptive statistics and econometrics model. Section three presents the empirical results of the study whilst the final section presents conclusion of the study.

2. ESTIMATION METHODS

2.1 Descriptive statistics

In this section, descriptive statistics was one of the techniques used to summarize the data collected from the sample respondents. Therefore, it was used to the associate different institutional as well as demographic and socio economic characteristics of respondents with different repayment status categories. For these reasons frequency, percentages, means and standard deviations were used.

2.2 Multinomial logistic regression

Multinomial logistic regression is used to predict categorical placement in or the probability of category membership on a dependent variable based on multiple independent variables which could be either dichotomous or continuous (Starkweather and Moske, 2011). Thus,

ISSN: 2278-6236
Impact Factor: 6.943

multinomial logit model explains the relationship between dependent outcome variable and one or more independent variables.

According to O'Halloran (no date), multinomial logit model is often considered as an attractive analysis as it does not consider normality, linearity or homoscedasticity assumptions. However, other than these, multinomial regression does have a number of assumptions (Starkweather and Moske, 2011).

Assumptions

a. Independence among the dependent variable choices: this assumption states that the choice of or membership in one category is not related to the choice or membership of another category (Starkweather and Moske, 2011).
b. Assumption of independence of irrelevant alternatives (IIA): postulate that the inclusion or exclusion of categories does not affect the relative risks associated with the regressors in the remaining categories (Williams, 2016).
c. Test of independent variables: with J dependent categories, there would be J–1non redundant coefficients associated with each independent variables x_k. The hypothesis that x_k doesn't affect the dependent variable can be written as:

$$H_0: \beta^1_k = \beta^2_k = ---------- = \beta^J_k$$

where β^1_k, β^2_k, ----------, β^J_k are parameters of 1, 2, ------, J categories relative to the base group (Freese and Long, 2000).
d. Assumption of multicollinearity: it occurs when two or more independent variables in the model are approximately determined by a linear combination of other independent variables. The degree of multicollinearity can vary and have different effects on the multinomial model (Freese and Long, 2000; Schofer, 2007).

Therefore, before using the multinomial model to make any statistical inference, there is a need to check the model of these assumptions.

Multinomial logistic regression is a simple extension of binary logistic regression (Starkweather and Moske, 2011).In this model, the outcome variable is loan repayment status of clients of ACSI and takes on categories 'paid on time', 'delinquency' and 'default on loan' which are indexed as 1, 2 and 3. On top of these, depending on theoretical, empirical studies and institution specific contexts, the study has incorporated different independent variables which affect the loan repayment performance of clients of ACSI.

Let π_{ij} = Pr (Y_i= j) (1)

Equation (4.1) denotes the probability that the i^{th} response that falls in the j^{th} category. According to Freese and Long (2000), Schofer (2007) and Rodriguez (2007), if response categories are mutually exclusive and exhaustive, probability of i^{th} response that falls in the j^{th} category must add to 1.

$\sum_{j=1}^{J} \pi ij = 1$ (2)

Perhaps, the simplest approach to multinomial data is to choose one of the response categories as a baseline or reference outcome that serves as contrast point for all analyses (Rodriguez, 2007; Hegre, 2011). According to Freese and Long (2000), by default the base category would be the one with the largest number of cases. In the study, there are 200 cases for category 'paid on time' and hence, *Stata* was told to make it as reference category. Furthermore, after assigning base category, there is a need to calculate log-odds for all other categories relative to the baseline category which has to be a linear function of the predictors (Rodriguez, 2007; Khan, 2010).

Having the above, the model can simultaneously estimates the following binary logit models among all pairs of outcome categories.

$\ln \frac{\pi i2}{\pi i1} = \beta_0{}^2 + \beta_1{}^2 x_1 + \beta_1{}^2 x_2 + \dots\dots\dots + \beta_{14}{}^2 x_{14}$ (3)

$\ln \frac{\pi i3}{\pi i1} = \beta_0{}^3 + \beta_1{}^3 x_1 + \beta_1{}^3 x_2 + \dots\dots\dots + \beta_{14}{}^3 x_{14}$ (4)

Where ($\beta_0{}^2$, $\beta_1{}^2$,……, $\beta_{14}{}^2$ and $\beta_0{}^3$, $\beta_1{}^3$,………,$\beta_{14}{}^3$) are parameters of outcome categories delinquents relative to paid on time and defaulters relative to paid on time clients whereas (x_1,x_2,………,x_{14}) are independent variables in the above outcome categories.

However, equation (4.3) and (4.4) are analogous to a logistic regression model, except that the probability distribution of the response categories is multinomial instead of binomial. In addition, we have J − 1 equations which is two instead of one. On the other hand, equation (4.3) and (4.4) contrast categories 2 versus 1 and 3 versus 1 and the missing contrast between categories 2 and 3 can easily be obtained in terms of the other two categories (Freese and Long, 2000; Rodriguez, 2007; Hegre, 2011).

$\ln \frac{\pi i2}{\pi i3} = \ln \frac{\pi i2}{\pi i1} - \ln \frac{\pi i3}{\pi i1}$ (5)

Moreover, the multinomial logit model may also be written in terms of predicted probabilities (Rodriguez, 2007; Hegre, 2011).

$$\Pr(y=1) = \frac{1}{1 + e^{X\beta(2)} + e^{X\beta(3)}} \quad (6)$$

$$\Pr(y=2) = \frac{e^{X\beta(2)}}{1 + e^{X\beta(2)} + e^{X\beta(3)}} \quad (7)$$

$$\Pr(y=3) = \frac{e^{X\beta(3)}}{1 + e^{X\beta(2)} + e^{X\beta(3)}} \quad (8)$$

Where: $\beta^{(1)} = 0$

$e^{X\beta(2)}$ and $e^{X\beta(3)}$ are exponential functions of equation (4.3) and (4.4) in matrix form.

The relative probability of *y* = 2 (delinquents) to the base outcome y = 1 (paid on time) is

$$\frac{\Pr(y=2)}{\Pr(y=1)} = e^{X\beta(2)} \quad (9)$$

The ratio denoted by equation (4.9) is the Relative Risk Ratio (RRR) which is probability of choosing one outcome category over the probability of choosing the baseline category. Thus, it is obtained by exponentiating the coefficients of the linear regression equations.

3. DESCRIPTION OF VARIABLES OF THE MODEL

There are numerous variables which are important to loan repayment performance of clients. Depending on theoretical, empirical works and institution specific contexts, the study incorporated different variables which simultaneously affect loan repayment performance of clients of ACSI. Therefore, the variables that are incorporated ranges from demographic characteristics of borrowers to that of institutional characteristics of ACSI.

In general, the variables incorporated in the model were classified in to outcome categorical variables and independent variables.

Outcome categorical variables

Repayment performance of clients: This outcome variable was classified into three categories namely 'paid on time' for the clients who repaid loan before the due date, 'delinquency' for clients who repaid late from the due date or repaid less than the appropriate amount of their most recent loan, and 'default' for the clients who did not pay after three months of the due date(Nawai and Shariff, 2012). Further, this variable is measured as a dummy variable taking the value of 1 if the respondent paid the loan on time, 2 for delinquency and 3 for default on loan.

Independent variables

Sex of the respondent: There is a belief that female are better payers than male borrowers taking in to consideration their being more entrepreneurial that results from assuming more responsibilities in the internal affairs of a household (Vigano, 1993 cited in Fikirte, 2011). As a result, they can perform their business independently and repay their loan on time. On the other side, the variable is measured as a dummy variable taking the value 1 if the respondent is male and 0 otherwise.

Age of the respondent: This variable also affects loan repayment performance. Fikirte (2011)noted that with increase in age, it is usually expected that borrowers get more stability and experience on their business. Hence, they may able to generate income that leads to high repayment performance. In addition, the variable age is measured on a continuous scale in terms of respondent's number of years of age at time of data collection.

Education level of the respondent: A more educated client is expected to use the loan effectively as compared to a less educated one. In line with this, educated borrowers may develop the entrepreneurial skill and they may engage in a new business (Pasha and Tolosa, 2014; Ashhari and Nassir, 2015).On the other hand, it is measured as a dummy variable taking the value 1 if the respondent attends primary education, 2 if the respondent attends secondary high school and 3 if attends higher education which consists of certificate, diploma and above at time of data collection.

Family size and number of dependents of the respondent: If the respondent has a large number of family members, they need more income in order to cover the expense of their household members. Therefore, the borrower may use the loan directly for their daily consumption and other expenses which in turn increases the default rate. On the other hand, number of dependents is the number of nonworking members of the family (Fikirte, 2011; Firafis, 2015).

Loan size: If the amount of loan released is enough for the purposes intended, it will have a positive impact on the borrower's capacity to repay. In other word, the higher the total loan received by the borrowers, the higher probability of borrowers to pay their loan on time. This is because the borrowers have enough funds to finance their business that makes them get more profit and increase their business profile(Nawai and Shariff, 2012; Pasha and Tolosa, 2014; Ashhari and Nassir, 2015). Thus, this variable is measured in Ethiopia Birr (ETB)[1].

[1] ETB is Ethiopian Birr which is the currency of the country; 1 US$ = 22.69 ETB as of March, 2017 exchange rate.

Time laps between loan application and disbursement: Timely disbursement of loan increases the borrowers' loan repayment ability. Therefore, this positive precondition enables borrowers to enhance better loan repayment performance (Pasha and Tolosa, 2014).Furthermore, this variable is measured in terms of number of days it takes in collecting the loan from time of application.

Interest rate: This variable has a great influence on the loan repayment performance. It is further explained that an increase in interest rates on credit facilities advanced to the borrowers is likely to deter them from servicing their loans according to the agreed terms and conditions (Kariuki and Ngahu, 2016).

Loan tenure: Longer repayment period can be disadvantageous to borrowers which means that a borrower might be tempted to spend higher net income in the early months of the loan. This will in turn results in potential difficulty in making loan repayment for the later months(Ashhari and Nassir, 2015). Thus, this variable is measured in terms of number of months.

Training: If the lender provides training facilities, the clients will be able to understand the rule and regulations easily. They also develop skill on how to do a business and money utilization (Fikirte, 2011). Pasha and Tolosa (2014) also agree on the importance of well-organized and sufficient training so as to improve loan repayment performance. Further, this variable is measured as a dummy variable taking the value 1 if the respondent attended training before taking the loan and 0 otherwise.

Business experience: A business run by an experienced person has an effect on the loan repayment performance. The risk of failure is less, when the business operated by experienced person than those who have just started (Fikirte, 2011). Therefore, the more the number of years in a business, the better would be the loan repayment performance (Ashhari and Nassir, 2015). In addition, this variable is measured in terms of number of years.

Distance: Distance of borrower's business premise with lender office will influence loan repayment performance of clients. Being closer to lenders office, will give extra advantage to the lender and the borrower (Nawai and Shariff, 2012). This is because loan officers could easily make continuous supervision as well as advisory visits on the way of borrowers' loan usage and loan repayment (Pasha and Tolosa, 2014).On the other side, this variable is measured in terms of minutes that it takes from clients' business premise with lender office.

Monthly sale: Borrowers who earned more profit from their total monthly sale are more creditworthy and capable of repaying loan on time (Nawai and Shariff, 2012). Thus, the variable is measured in the analysis in terms of ETB.

Additional monthly income: It is believed that respondents' additional source of income could influence loan repayment performance of clients. This is because borrowers could have enough funds to finance their business that makes them get more profit (Firafis, 2015).Therefore, this variable is measured in terms of ETB.

4. RESULT AND DISCUSSION

4.1 Descriptive statistics analysis

Age of sample respondents ranges from 18 to 62 years with mean age of 34.36 years. Accordingly, the mean age of delinquents and defaulters were 33.85 and 33.54 years which were lower than the mean age of clients with no repayment problem that was 34.99 years. Thus, these indicate that the borrowers at younger stages became more defaulter than at older age which enables the elder borrowers to be better payers than youngsters.

Average family sizes of respondents were 3.07. Of these, the average family sizes of delinquents and defaulters were 3.05 and 3.24, while it was 3.01 for borrowers with no repayment problem respectively. Therefore, based on these the average family size of delinquents and defaulters are greater than the average family size of clients with loan paid on time. On the contrary, the average number of dependents for delinquents and defaulters were 0.90 and 0.92 which were lower than 0.94 average numbers of dependents for clients with loan paid on time.

On the other hand, with regard to loan disbursement time, it took respondents on average 20.92 days to collect the loan from ACSI. Of these, it took on average 23.11, 19.16 and 18.09 days for paid on time clients, delinquents and defaulters while collecting their loan from ACSI respectively. From survey result, the number of days it took for non-defaulters[2] were higher than those defaulters.

Lending rates of ACSI for sampled respondents range between 11% to 18% flat rate per year and on average, respondents were charged with interest rate of 17.35% per year.

[2] The term non-defaulters here was used to refer to clients with loan paid on time

Furthermore, non-default clients were charged interest rate of 17.29% on average which was lower than the other two categories. As a result, as has been explained, lower interest rate on credit facilities is likely to encourage borrowers to service their loans according to the agreed terms and conditions.

With respect to loan tenure, loan tenure for paid on time clients, 29.31 days, was found to be higher than the average loan tenure of all respondents and other two categories. These survey outcomes were in agreement with the advantage of longer repayment period that in turn results in better loan repayment performance.

On top of these, loan size of sample respondents range from ETB266.7 to ETB 100000 with mean loan size of ETB 13415. Accordingly, the mean loan size for delinquents and defaulters were ETB 12798.8 and 16574.6 which were higher than the mean loan size received by clients with no repayment problem that was ETB 12560.2. Thus, these survey results were not in agreement with the higher the total loan received by the borrowers, the higher probability of borrowers to pay their loan on time. On the other side, the survey results showed that the average business experience of non-defaulters was 6.89 years with maximum and minimum of 0 and 35 years of experience respectively. To the opposite, the average business experience of delinquents and defaulters were 6.92 years and 5.95 years respectively. In addition, the study has identified about 20% of respondents had 10 and above years of business experience, whereas 80% of them had less than 10 years of experience. Therefore, non-defaulters had more years of business experience than defaulters.

With respect to distance of business premise of borrowers with the nearby ACSI branch office, it took paid on time clients 33.88 minutes on average to reach the nearby office which was found to be higher than the average distance of premise of sample respondents and other two categories which were 29.94, 27.88 and 27.74 minutes respectively. However, these survey finding contradict with the hypothesis that the closer the lender office, the higher possibility of borrowers to repay their.

Average monthly sale of respondents were ETB 4835.9. Of these, the average monthly sale of delinquents and defaulters were ETB 4584.8 and 5544.8, whereas it was ETB 4712.7 for paid on time borrowers respectively. Therefore, the result shows that the higher the total monthly sale the higher would be the probability of borrowers to pay their loan on time.

This is because the borrowers have enough funds to finance their business that makes them get more profit.

Furthermore, households' source of income position and resource ownership was found to be important in loan repayment performance. Hence, the average source of monthly income of sample respondents was ETB 3794.6 with maximum and minimum monthly income of ETB 30000 and ETB 300. Furthermore, on average, non-defaulters had higher monthly additional source of income (about ETB 3680.5) as compared to delinquents that

Variables	Paid on time N = 200		Delinquents N = 122		Defaulters N = 78		Total N = 400	
	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
Age	34.99	7.91	33.85	10.13	33.54	7.91	34.36	8.65
Family size	3.01	2.01	3.05	1.99	3.24	2.12	3.07	2.02
Dependents	0.94	0.93	0.90	0.83	0.92	0.88	0.92	0.89
Loan size	12560.2	13622.6	12798.8	16085.7	16574.6	19442.5	13415.8	15697.3
disbursement	23.11	26.90	19.16	10.69	18.09	13.13	20.92	20.82
Interest rate	17.29	1.44	17.47	19.50.40	17.31	1.45	17.35	1.43
Loan tenure	29.31	8.89	25.76	9.51	25.97	8.76	27.58	9.20
Experience	6.89	6.89	6.92	6.51	5.95	4.61	6.71	5.81
Distance	33.88	55.81	27.87	44.61	20.74	20.15	29.49	47.55
Monthly sale	4712.71	9741.02	4584.75	5715.47	5544.81	7416.70	4835.94	8244.50
Income	3680.52	2879.85	3814.01	3731.48	4056.70	3711.39	3794.58	3322.23

was ETB 3814 but lower than defaulters who had on average ETB 4056.7.

Table 1: **Mean and standard deviation values for continuous variables**

Source: Own computation, 2017.

With respect to sex composition, 220 (55%) were female respondents, whereas, 180 (45%) were male respondents. The proportion of non-defaulters 97 (48.5%) were females borrowers whereas 103 (51.5%) were male counter parts. Furthermore, out of 122 delinquents 57.38% were female borrowers. Correspondingly, 67.95% of defaulters were female clients out of the total 78. This revealed that from their respective sex composition, male respondents were found having more repayment performance than female respondents contradicting creditworthiness hypothesis of female clients.

From the total, 29.5% of respondents attended primary education, 23%secondary high school and41.5% respondents attended higher education consists of diploma and above. On the other side, the educational level of non-defaulters were: 25% primary, 18.5% secondary high school, and56.5% were diploma and above, while for defaulters 30.77% primary, 30.77% secondary high school, and38.46% respondents were diploma and above.

These survey finding had positive implication on managing the business and in repaying the loan on time.

In order to effectively implement what the members of MFIs planned, training plays a significant role (Firafis, 2015). In this regard, out of the total 400 respondents 61.75% of them reported that they attended training while the rest 38.25% did attend the training sessions delivered by ACSI branch offices. For instance nearly 50% of paid on time clients reported that they attended training sessions of ACSI which was delivered on how to run a business and about different microfinance services of ACSI.

Table 2: Frequency and percentage results of dummy variables

Variables		Paid on time N = 200		Delinquents N = 122		Defaulters N =78		Total N =400	
		N	%	N	%	N	%	N	%
Sex	Male	103	51.5	52	42.62	25	32.05	180	45
	Female	97	48.5	70	57.38	53	67.95	220	55
Education	1	50	25	44	36.07	24	30.77	118	29.5
	2	37	18.5	31	25.41	24	30.77	92	23
	3	113	56.5	47	38.52	30	38.46	190	41.5
Training	Yes	99	49.5	90	73.77	58	74.36	247	61.75
	No	101	50.5	32	26.23	20	25.64	153	38.25

Source: Own computation, 2017

4.2 Econometrics results analysis

Here, econometric analysis was carried out in order to identify factors that affect loan repayment performance of clients of ACSI. As previously explained, multinomial logit model was employed to estimate the effect of hypothesized independent or explanatory variables on the loan repayment performance of beneficiaries in ACSI.

Out of fourteen variables hypothesised to affect loan repayment performance of borrowers, seven variables were found to be statistically significant for delinquents and five variables for defaulters. The maximum likelihood estimates of multinomial logistic regression model showed that age, education level, loan size, interest rate, loan tenure, training and monthly sale were factors affecting loan repayment performance of delinquent borrowers of ACSI. On the contrary, sex, loan size, interest rate, loan tenure and training were found to be factors affecting loan repayment of defaulters of ACSI.

On the other hand, RRR of seven explanatory variables namely, sex, family size, number of dependents, disbursement time, business experience, distance and monthly income were less powerful in explaining loan repayment performance of delinquents. Whereas for defaulters, nine variables namely, age, education level, family size, number of dependents, disbursement time, business experience, distance, monthly sale and additional source of income were found to be less powerful in explaining their repayment performance. In what follows, the results of the model estimates are interpreted in relation to each of the statistically significant variables.

In total, fourteen independent variables were used for estimation. To analyse factors influencing the loan repayment performance of borrowers of ACSI, multinomial logit model was estimated using *Stata version 11.2* statistical package.

4.2.1 Model summary

The study has used 400 observations, from clients of ACSI, in the estimation of multinomial logistic regression. The statistics, -372.31795, is the log likelihood of the fitted model which was used in the Likelihood Ratio Chi-Square test of whether coefficients of all explanatory variables in the model were simultaneously zero.

On the other hand, the Likelihood Ratio Chi-Square test for both binary logit models (delinquents relative to paid on time and defaulters relative to paid on time), LR chi2(30), indicates that at least one of the regression coefficient of predictors was not equal to zero. Therefore, the number in the parentheses indicates the degrees of freedom of the Chi-Square distribution used to test the LR Chi-Square statistic and was defined by the number of models estimated (2) times the number of predictors in the model (15).

Furthermore, Prob >chi2 indicates the probability of getting a LR test statistic. In other words, this was the probability of obtaining the chi-square statistic (77.38) if there was no effect of the predictor variables. Further, the p-value was compared to a specified alpha level, our willingness to accept a type I error, which was typically set at 1% or 5%. This would lead us to conclude that at least one of the regression coefficients in the model was not equal to zero and hence, the model as a whole fits significantly better than an empty model. In addition, the McFadden’s pseudo R-squared of the multinomial logistic regression was 9.4%.

4.2.2 Interpretation of RRR of delinquents and defaulters relative to clients with loan paid on time

In this section, the multinomial logistic regression was interpreted in terms of relative risk ratios[3] and hence can be obtained by exponentiating the multinomial logit coefficients, e^{coeff}.

As has been described, the outcome categories in the estimation were clients with loan paid on time, delinquents and default clients. Thus, the entire analysis focused on the relationship of these outcome categories with a number of independent variables that ranges from demographic to institution related characteristics. To do so, the *Stata* chose the most frequently occurring group, loan paid on time, as the base category.

Sex of the respondent (sex): This relative risk ratio compares male to female clients for defaulters to clients who paid their loan on time given that the other independent variables in the model are held constant. In this regard, for males relative to female clients, the relative risk for defaulters relative to paid on time would be expected to decrease by a factor of 0.507with 5% level of significance.

This finding showed that female borrowers have higher probability of being in the default category. Hence, it contradicted with most previous results that found female borrowers as more creditworthy than male borrowers. But, the result was in agreement with the findings of Fikirte (2011) and Nawai and Shariff (2012).

Age of the respondent(age): Here, given a one year increase in age of the respondents, the relative risk of being in the delinquency group would be 0.947 times less likely. More generally, if clients were to increase their age, they would be expected to fall into paid on time category as compared to delinquency category with 5% level of significance. In addition, this finding was in line with the findings of Fikirte (2011), Pasha and Tolosa (2014) and Firafis (2015).

Education level of the respondent (education): The relative risk ratio of this variable compares clients with higher education level to those with primary education for delinquents to clients who paid their loan on time given that the other independent variables in the model are held constant. Therefore, the relative probability of being delinquent rather than being client with loan paid on time was 46% lower for clients with higher education level relative to clients with primary education which was significant at 5%.This finding was consistent with the hypothesis that higher educational level will lead to

[3] See coefficient estimate of multinomial logit model in the appendix part.

better loan repayment performance. In addition, the result was in agreement with Nawai and Shariff (2012), Pasha and Tolosa (2014) and Ashhari and Nassir (2015).

Loan size (loan size): This multinomial logit estimate shows that a one ETB increase in the size of loan for both delinquents and defaulters relative to paid on time category given that all other variables are held constant. So that, if a subject were to increase their loan size by one ETB, the relative risk for delinquents relative to paid on time clients would be expected to increase by a factor of 1.002. On the other side, the relative risk for defaulters relative to paid on time clients would be expected to increase by a factor of 1.003 with 10% level of significance for both comparison categories.

These results contradicted with the findings of Nawai and Shariff (2012), Pasha and Tolosa (2014) and Ashhari and Nassir (2015).However, if the amount of loan exceeds what the borrower needs and can handle, it would be more of a burden than help as it goes to personal use, thereby undermining repayment performance(Norell, 2001 cited in Fikirte, 2011).

Interest rate (interest): If ACSI were to increase interest rate by one percent, the relative risk for delinquency category relative to paid on time category would be expected to increase by a factor of 1.406whereas the risk for defaulters relative to paid on time category would be expected to increase by a factor of 1.218given the other variables in the model are held constant. Therefore, the relative risk of being in the delinquency group would be 1.406and of being in default category would be 1.218 times more likely when ACSI increases interest rate on borrowed fund by one percentage which was significant at 10%. These findings were consistent with findings of Kariuki and Ngahu (2016).

Loan tenure(tenure):This is the multinomial logit estimate for a one unit increment in loan tenure for both delinquent and default borrowers relative to borrowers paying on time. Consequently, if ACSI were to increase loan tenure by one month, the multinomial log-odds for preferring delinquency to paying loan on time would be expected to decrease by a factor of 0.964. On the other hand, the multinomial log-odds for preferring default to paying loan on time would be expected to decrease by a factor of 0.963 as ACSI did the same. The variable became significant predictor of borrowers' loan repayment performance at 5% and 10% level of significance for both comparison categories respectively. In addition, these finding was in agreement with findings of Pasha and Tolosa (2014) as it contradicted with the hypothesis of disadvantage of longer repayment period. But, the finding was inconsistent with the findings of Ashhari and Nassir (2015).

Training (training):This relative risk ratio compares clients who attend training to clients who did not for both delinquents and defaulters relative to referent group clients who paid their loan on time given other independent variables in the model are held constant. In this regard, the relative probability of being at delinquency rather than paying loan on time for clients who attended training was more than double the corresponding relative probability for clients who did not (which was 2.398 at 1% level of significance). On the other hand, the relative probability of being default rather than paying loan on time for clients who attended training was more than double (2.132 times) the corresponding relative probability of clients who did not at 5% level of significance.

However, this finding contradicted with the previous findings that delivery of well-organized and sufficient training by MFIs would improve loan repayment performance. The possible explanation would be lack of training programs that primarily focused on how to market products, financial management and account recordings as of 47.5% of respondents reported that these programs by branch offices solely lack business oriented sessions.

Monthly sale (sale):This was the relative risk ratio for one ETB increments in the monthly sale of clients for delinquents relative to paid on time clients. Thus, if a subject were to increase the monthly sale by one ETB, the multinomial log-odds for being delinquent to paying on time would be expected to decrease by a factor of 0.999 which was significant at 5%.Furthermore, in terms of total sales, the result shows that borrowers who earned more profit are more creditworthy borrowers. The result was in line with the study that has been done by Nawai and Shariff (2012).

4.2.3 Tests for assumptions of multinomial logit model

Multinomial logistic regression is often considered an attractive analysis (Starkweather and Moske, 2011). However, multinomial logistic regression does have tests for model fit such as test of independent variables, test of independent irrelevant alternatives (IIA), test for combining dependent categories (Freese and Long, 2000; Starkweather and Moske, 2011; Williams, 2016) and test of multicollinearity problem(Starkweather and Moske, 2011). When such tests of multinomial logit analysis are not met, the analysis may have problems and these problems may lead to invalid statistical inferences. Therefore, before the use the model to make any statistical inference, it was a must to check that our model fits sufficiently well.

Table 3: Regression outcomes of the multinomial model

Repayment type	Delinquents			Defaulters		
	RRR	Std. Err.	P>|z|	RRR	Std. Err.	P>|z|
Paid on time	**(base outcome)**					
sex	.7190649	.1951726	0.224	.5068957	.1633167	0.035**
age	.9466965	.0222359	0.020**	.9696644	.0257044	0.245
education						
2	.6044842	.2351944	0.196	.9159861	.3949577	0.839
3	.4590098	.1682187	0.034**	.6983634	.2949804	0.395
family size	.9918271	.1059734	0.939	1.143168	.139469	0.273
dependents	.8629642	.1793227	0.478	.7509962	.1804095	0.233
loan size	1.002015	3.6900106	0.057***	1.003016	4.0400106	0.053***
disbursement	.9858777	.0102144	0.170	.9801283	.0123932	0.112
interest	1.406403	.1469846	0.001*	1.218423	.1373665	0.080***
tenure	.9643508	.0165604	0.035**	.9626439	.0189825	0.054***
training	2.398806	.796302	0.008*	2.231619	.8523987	0.036**
experience	1.049922	.0331486	0.123	.9856751	.0385574	0.712
distance	.9964072	.0028053	0.201	.9903947	.0069807	0.171
sale	.9999549	.0000219	0.039**	.9999733	.0000205	0.193
income	1.000052	.0000489	0.285	1.000056	.0000512	0.272

Log likelihood = -372.31795
Number of obs = 400
LR chi2(30) = 77.38
Prob > chi2 = 0.0000
Pseudo R2 = 0.0941

Note: * significant at 1%, ** significant at 5% and *** significant at 10%

Source: Own computation, 2017

Test of independent variables

To test this assumption[4], there was a need to estimate a series of models by storing the results. In addition, the study has used *Wald* test for each independent variables in the model as likelihood ratio tests took long time. As has been shown, the model of the study fulfils this test of independence among predictors as all coefficients associated with significant variable(s) of the model were different from zero.

Test for Independence of Irrelevant Alternatives (IIA)

[4] Tests of all these assumptions are found in the appendix part.

With respect to this assumption, all three outcomes of the model were fit and then results are stored under the name *allcats.* As a result, the study re-estimates the parameters by excluding the most-frequent category (paid on time outcome) and performs the *hausman* test against the fully efficient full model. Therefore as has been shown, there was no evidence that the IIA assumption has been violated.

Test for combining dependent categories

According to Williams (2016), if none of the independent variables significantly affects the odds of pairs of outcome, it was possible to conclude that these pairs of outcomes were indistinguishable with respect to the variables in the model. Based on the output of combining categories test, the study saw that no categories should be combined.

Test of assumption of no multicollinearity

Therefore, so as to check this assumption, the study used two common measures which are tolerance (an indicator of level of collinearity a regression analysis can tolerate) and VIF (Variance Inflation Factor) respectively. The VIF values were found to be very small (much less than 10) indicating absence of multicollinearity among variables. Likewise, the result of the computation of tolerance level revealed that there was no serious problem of association among variables as it was much above 0.1. Thus, as has been shown in the appendix, the model has no any concern of issue of multicollinearity**.**

5. CONCLUSION

The main problem of the poor performance of financial institutions in many developing countries is high rate of non-repayment of loan(Fikirte, 2011). This study was intended to identify the determinants of loan repayment performance of ACSI. In order to identify the factors affecting loan repayment performance descriptive statistics and multinomial logit model were employed.

Out of fourteen variables hypothesised to affect loan repayment performance of borrowers, eight variables were found to be statistically significant. The maximum likelihood estimates of multinomial logit model showed that sex, age, education level, loan size, interest rate, loan tenure, training and monthly sale were factors affecting loan repayment performance of borrowers of ACSI.

The regression outcomes indicated that male borrowers and elder respondents have better repayment performance than female borrowers and youngsters. Therefore, study recommends that, even though ACSI is working hard to increase participation of females and youngsters, great care must be taken starting from screening of applicants to repayment periods. In addition, the institution should motivate educated people as education level had positive sign in the loan repayment performance.

Loan tenure was found to be a significant determiner of loan repayment performance. Therefore, the institution has to give enough time to clients so that they will be able to work with the loans and arrange the time to collect loan that will be suitable for them. On the other hand, the study found that improvement in total sales will increase the loan repayment performance which has to be accompanied by continuous and strong follow up. On the contrary, loan size negatively affects loan repayment performances. Hence, it is recommended that institution should compute thoroughly the borrowers' business proposal loan size before approving.

Further, the finding regarding training variable contradicted with the previous findings that delivery of well-organized and sufficient training by MFIs would improve loan repayment performance. Hence, it is recommended that there is a need to deliver training sessions which solely focused on typical business of clients.

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