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Modeling the Propensity to Default on Microloans in Mali, Africa

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Microfinance is a global phenomenon that is focused on sustainable poverty alleviation. By providing people in developing countries with the capital to sustain themselves and an educational background on which to build their futures, microfinance institutions (MFIs) give the poor an opportunity to get out of poverty. This study utilized a specific MFI in Mali, Africa to model the propensity for borrowers to default on microloans. Using the MFI's historical data, the purpose of this study is to model the repayment percentage of individual loans, contingent upon qualitative and quantitative factors. An Ordinary Least Squares Model is used to analyze how each independent factor influences default rates. Factors that contribute to high default rates are grouped together using fuzzy analysis. I hypothesize that high default rates were encouraged by a longer time between payments, a large initial loan size, development of business in investment-heavy industries, and in a hostile market environment. These results indicate that the MFI can optimize its loan repayment success by targeting specific borrowers and modifying their loan structure. The results of this study suggest tangible practices the Mali MFI can utilize to increase their loaning effectiveness.

Introduction

Microfinance is a global phenomenon that is focused on sustainable poverty alleviation. By providing people in developing countries with the capital to sustain themselves and an educational background on which to build their futures, microfinance institutions (MFIs) have given the poor an opportunity to get out of poverty. These loans are un-collateralized and thus depend on character-based lending. MFIs strive to decrease poverty in their location of business, so they focus on reaching out to the poor who have entrepreneurial potential. In the developing world, sound financial institutions are difficult to come by, and those that do exist require high credit scores and collateral for loans. Microfinance seeks to combat this structural disadvantage of the poor by providing them with the means to succeed in a small business (Grameen Bank, 2012).

Mali is a vibrant country, however, it suffers from extreme poverty. Mali is one of the 10 poorest countries in the world; their GDP per capita in US dollars is $531 (Central Intelligence Agency, n.d.) Historically, MFIs evidence some common trends; for example, about 80% of worldwide microloans are given to women due to their superior repayment history and their dedication to improving their families with the money they earn. Many MFIs also utilize group loans to increase repayment rates because of the peer pressure and social compulsion to repay the loans. These group-lending MFIs boast about a 96% worldwide repayment rate (CGAP, n.d.) The Mali MFI data analyzed in this study represent some group loans, but most are individual loans.

The Mali MFI is small and new to the microfinancing world. It is, therefore, important that they collect and analyze data to improve their repayment rate performance and their effectiveness in helping the poor. Much of the literature dedicated to microfinance does not analyze default rates and there is a lack of microfinance study in Mali. Fuzzy analysis has also never been utilized to investigate grouped factors that impact default rates. Kurosako and Khan (2012) studied default rates for microloans in Pakistan and observed that default rates have high explanatory power in the success of joint liability loans among the poor (p. 83). Consistent with economic theory, Pande and Field (2008) found that a more lenient repayment schedule lowers transaction costs and does not increase default rates (p. 510).

This study adds to the existing literature by modeling the repayment percentage of individual loans, contingent upon personal and monetary factors. The literature suggests that certain institutional rigidities of microfinance markets held them back in the past from reaching their full potential for poverty alleviation (Hertz-Bunzl, 2006; Kaladhar, 1997). Certain design features of the lending process could be changed to ensure more borrower success (Kaladhar, 1997). This study looks specifically at what those rigidities and design features could be. The economics and microfinance literature supports the notion that microfinance can be a key component in poverty alleviation, specifically for women and people in developing nations (Khandker, 2005).

An Ordinary Least Squares (OLS) Model is used to analyze the influence of independent factors on default rates. This method is ideal for analyzing various rigidities within this specific micro-lending framework, whether it be that the loans are too large, the interest rate is too high, or the type of businesses they are supporting are unsuccessful. Fuzzy analysis is used to group together factors that contribute to high default rates as a collective. This is a powerful type of analysis used to identify the significance of groups of variables rather than individual variables. In the current study, fuzzy analysis allows for the analysis of groups of variables that can support suggestions for improvement of default rate by changing many variables rather than just one. The hypothesis in this study is that high default rates are encouraged by a longer time between payments, a large initial loan size, business development in investment-heavy industries, and starting a business in a hostile market environment. The purpose of this study is to provide the Mali MFI with tangible results it can utilize to increase its loan effectiveness.

Theoretical Issues of Microfinance Studies

Microfinance is a relatively new field and the formal literature surrounding it is new and growing. Microfinanciers have tailored their loan style to specific groups and to meet the needs of the poor in the geographical area in question. Through trial-and-error, as well as through knowledge of poverty, MFIs have developed what lenders think will best meet the needs of these borrowers. Data collected by MFIs reveal trends that suggest certain groups and loan styles will be more successful with microloan borrowing than others, and formal research indicates that some of these suggested practices have statistical significance (Balasubramanian, 2009; Hermes & Lensink, 2007; Kaladhar, 1997). Many microfinance institutions feel they have to walk a fine line by providing community development programs and financial services (Hermes & Lensink, 2007; Vanroose, 2008).

Over 80% of worldwide micro-borrowers are women. Microfinance institutions have observed that women micro-borrowers are successful in helping their families because they spend their money on investing in their future and those of their children. Statistically, women more than men spend their profits on education for their children, healthcare, and infrastructure for their houses (Opportunity International, n.d.). These findings suggest that microfinance loans may be more successful when given to women (Leach & Sitaram 2002; Vonderlack & Schreiner, 2002).

Because many micro-borrowers have no previous experience with borrowing money, many practitioners suggest that having strict repayment schedules will help the borrowers develop fiscal responsibility by constantly holding them accountable for repaying their loans. Some suggest that 1–2 weeks between payment periods is not too frequent because borrowers make their loan more of a priority in their life meet with their loan officer or loan group more often (Grameen Bank, 2012). There is also extensive research that supports the MFI provision of regular repayment schedules because they act as effective enforcement mechanisms for loan repayment (Besley, 1995; Morduch, 1999; Morvant, 2007). However, some empirical studies have shown the opposite. For example, Pande and Field (2008) found that a more flexible repayment schedule does not increase default rates and actually leads to decreased transaction costs.

Economic theory suggests that collateralized loans ensure more successful loan repayment rates because the cost of defaulting on collateralized loans is much higher (Becchetti & Pisani, 2010). Therefore, many MFIs have incorporated a type of “cultural collateral” which is known as microfinance group lending. Groups are held collectively accountable for the repayment of their loans and their relationships among each other act as their loan collateral. The Grameen Bank has championed worldwide group micro-lending and suggests that group loans are the best way to ensure repayment and community involvement (Grameen Bank, 2012). This study tests which loan factors impact default rates for Mali MFI loans.

Data and Variables

Data were collected over a period of four years by an MFI in Mali, Africa. The data consist of 84 micro-borrowers and 111 individual loans. These loans spanned from just a few years to multiple months, there was detailed information about the timeliness of repayment as well as borrower characteristics. These data are from various locations in Mali and numerous types of businesses. The 84 borrowers represent 11 different ethnicities in Mali and 10 Malian cities, primarily in the central and the southwestern regions of Mali. Borrowers are mostly individual males and females, although some group loans are included. The borrowers comprise varied religious identities, including Protestant, Catholic, and Muslim, and their businesses include food service and clothing retail, animal husbandry, and solar oven construction. Various loan-specific variables included in the data are: status of the loan, loan principal, interest rate, amount overdue, amount of loan outstanding, amount written off (an amount that the MFI does not expect to receive back, typically due to an emergency situation), number of late and early payments, and the default rate (the dependent variable). The data also include whether or not there was violence in the marketplace during the period of the loan.

Summary Statistics

The summary statistics in Table 1[1] represent the significant variables that are included in the final model. The most statistically significant variables include "Location 4," which makes up 12% of the loan population; "Muslim," which makes up 7% of the loan population; and "Other Businesses," which includes 9% of the sample population. All of the statistically significant variables are dummy variables. If the loan has that characteristic, it has a 1 in the dummy variable column; if it does not have that characteristics, it has a 0.

Method

Ordinary Least Squares

The statistical software package STATA was utilized to analyze this data set. These data were collected from an internal MFI source that is not available to the public; they were collected and formatted into a cross-sectional data set.

An OLS model is used to analyze the contributing factors to default rate. Analyzing both quantitative and qualitative specifics to each loan, the OLS model is:

$$Y_i = \alpha + \beta CLW_i + \gamma CLM_i + \delta A_i + \eta IP_i + \varphi LO_i + \theta ETH_i + \psi LOB_i + \rho RE_i + \sigma RST_i + \kappa GEN_i + \lambda GR_i + \varsigma BUS_i + \mu_i$$

Where α is the intercept; CLW is whether or not the loan was closed and written off; CLM is whether or not the loan was closed and the obligations of the loan were met; A is whether or not the loan is active; IP is the set of varying interest and principle variables; LO is the set of office location variables; ETH is the set of ethnicity variables; LOB is the set of location of business variables; RE is the set of religion variables; RST is the set of relationship to the staff member variables; GEN is the set of gender variables; GR is whether or not the loan is a group loan; BUS is the set of business type variables; and μ_i is the error term. For purposes of this study, the natural log was calculated for every variable that was originally measured in

[1] All tables are located in the Appendix.

African Francs (principal of loan, amount written off, amount paid) to better assess the impact of the variable.

OLS regression analysis is used to examine the dependent variable—the default rate for each individual loan (Y). All of the variables that are in groups were tested for their group significance using a test of the null hypothesis that all variables are 0.

Fuzzy Analysis

Fuzzy-set analysis is also utilized to analyze these data. Fuzzy-set is a qualitative comparative analysis (QCA) that is a powerful new way to analyze multivariate data (Longest & Vaisey, 2008). QCA harnesses the power of Boolean logic to assess the correlation between the dependent variable, the default rate of each individual loan, and all binary combinations of multiple independent variables. This analysis provides specific combinations of independent variables that offer evidence that there are various pathways to reach certain outcomes. The inclusion ratio is used to evaluate the relationships in question:

$$I_{XY} = \Sigma\min(x_i,y_i)/\ \Sigma x_i$$

In fuzzy analysis, X is the predictor configuration, Y is the outcome set, x_i is each variable's place in the configuration of X, and y_i is each variable's place in the configuration of Y. The closer I_{XY} is to unity, the larger the consistency of the data with the statement "if X, then Y" (Longest & Vaisey, 2008). Each solution is then analyzed with respect to its coverage of the outcome. This coverage indicator measures how much of Y is covered by X:

$$C_{XY} = \Sigma\min(x_i,y_i)/\ \Sigma x_i$$

The coverage indicator calculates how much of the outcome is explained by examining the final solution set. Longest and Vaisey (2008) summarize the capacity of fuzzy-set analysis:

> the fuzzy program allows the user to create configurations from single sets coded as dichotomous or fuzzy, to evaluate the sufficiency of these configurations statistically by using a variety of benchmarks, and to reduce the configurations determined sufficient to their common logical elements. (p. 83)

I employ fuzzy-set analysis to examine the impact of groups of variables on the default rates.

Results

Analysis of all qualitative and quantitative variables pertaining to each individual loan indicates that many quantitative variables are insignificant ($p > .10$) in determining default rate. Quantitative variables include variables such as loan amount, interest rate, and loan duration. Qualitative variables include variables such as religion, location, type of business, and personal characteristics (Cassar & Wydick, 2010; Gine, 2007). Many of the variables discussed in the theoretical section of this paper are found to be insignificant, such as loan amount, thus making it difficult to comment on the existing theory of micro-lending. This is most likely due to the fact that the sample size is small with only 111 observations.

Significant variables identified in the model include status of the loan, location of the business, religion of the borrower, group loan, and type of business. All of the groups of variables were found, after statistical testing, to have noteworthy group significance. The "status of loan" group variables are compared to the "written off closed loan" variable that was not included in the model. All of the location variables are compared to location 8 (the exact locations cannot be disclosed because of non-disclosure agreement stipulations). The religion variables are compared to the Catholic variable, which is not included in the model. The significance of this type of social capital is supported by the literature (Cassar & Wydick, 2010). The "type of business" variables are compared to the animal husbandry variable that is also not included in the model. The OLS model explains 69.6% of the variation in the data; this could also be due to the fact that there are a large number of variables in the model. Although this comprehensive data set included a great deal of variables, there were many things that were not included in the data that could have influenced the variation in the data such as previous business experience and/or business help from family.

The regression results of the statistically significant variables indicate that any loan status, other than "written off closed loan," contributes to a lower default rate significantly. Importantly, loans to a micro-business in Location 4 have a 27% higher default rate than businesses in Location 8. Location 4 was the site of market raids that destroyed many of the marketplaces where micro-borrowers sold their goods. Market conditions in Location 4 were unstable and dangerous, which likely contributed to borrowers defaulting on their loans (James, Nadarajah, Haive, & Stead, 2012).

According to the results, group loans also had high default rates. Group loans were 23% more likely to be in default than individual loans, which is significant at the $p < .05$ level. This is an interesting finding because it runs counter to the advice of microfinance practitioners. Much research supports the notion that group lending creates a joint liability with loan repayment which, in turn, reduces information asymmetries (Hermes & Lensink, 2007). One explanation as to why group borrowers have a more difficult time repaying their loans is because this MFI in Mali caters primarily to individual borrowers. This specific MFI only takes on a few group loans, suggesting the MFI may not be tailoring their lending practices to group needs.

The “Muslim” variable is very significant; its coefficient shows that, if the micro-borrower is Muslim, they will have a 22% higher default rate than Catholic borrowers. This finding is consistent with the theory that Muslim borrowers may have a more difficult time with microloans because of religious practices regarding “interest-free” loans (Seibel, 2008). Another significant variable is “Food Retail.” Compared to “Animal Husbandry,” food retail businesses are 20% less likely to default on their loans. The regression results shed interesting light on what kinds of factors contribute to successful loan repayment rates for this MFI.

Fuzzy analysis was used for the grouped variables to determine the impact on the dependent variable of each variable group combination. The following “paths” identify combinations found to be conditions for low default rates. The first path is: if the loan is not given in Location 4, the borrower is not Muslim, it is not a group loan, and is not given to a business of type “other,” then the default rate is low. The second path to low default rates is: if the loan is not given in Location 4, the micro-borrower is not Muslim, the loan is not a group loan, and the business is in the “other” business. The third path is: if the loan is not given in Location 4, the micro-borrower is Muslim, the loan is not a group loan, and the business is not from the “other” category, then the loan default rate is low. The last path is: if the loan is not from Location 4, the borrower is not Muslim, the loan is a group loan, and it is not from the “other” business category, then the loan default rate is low. These paths make up combinations of significant variables and if a loan follows one of these paths, the loan will be less likely to end in default.

Regression Results

Table 2 shows the regression results for OLS model. This model includes the coefficient of each variable and their standard errors. A negative coefficient means that the variable contributes to a lower default rate. Variables that contribute to a lower default rate include obligation met, overpaid, active, location 1, location 4, Muslim, group loan, retail business, and other business.

Fuzzy Results

Table 3 displays the various fuzzy outputs and their significance. Each set is labeled with its path number. It appears that all of these combinations are significant. The four combinations are:

1: Location 4, Muslim, Group Loan, Other Business

2: Location 4, Muslim, Group Loan

3: Location 4, Group Loan, Other Business

4: Location 4, Muslim, Other Business

Each of these paths represents a combination of significant variables and how they contribute to the dependent variable as a group. Table 4 shows the various combinations of variables that make up conditions for a low default rate.

Conclusions

This study determined that there are numerous factors that are correlated with loan repayment rates in Mali, Africa; significant variables include obligation met, overpaid, active, location 1, location 4, Muslim, group loan, retail business, and other business. Because these variables are statistically significantly correlated with repayment rates, this suggests that micro-lenders could increase their borrower's lending success by encouraging them to pursue certain types of businesses (retail and other businesses) or focus on more successful areas to lend to (location 1 and location 4). The most significant contributing factors were not the quantitative variables, but the qualitative independent variables. The final model explains 69.6% of the variation in the data. The knowledge gained by this study may aid the Mali MFI in tailoring their loans in a more effective manner to increase their repayment percentage.

Study limitations include the scope and time frame of this study. Although the model explains 69.9% of the variation in the default rates, the data are from a small sample size. Additionally, the data for this study were collected over a short period of time from only one MFI. A cross-sectional study from many MFIs would yield more robust results, and data collected over a longer time period would benefit the implications of this study. Future studies may enable the Mali MFI to further their investigation in success metrics for the impact of micro-loans on poverty.

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Appendix

Table 1

MFI Loan Summary Statistics

Variable Name	Variable Description	Count	Average	Standard Deviation	Minimum	Maximum
clsd_writtenoff	Closed and written off loan	28	0.25	0.44	0	1
clsd_oblmet	Closed loan with obligations met	35	0.32	0.47	0	1
overpaid	Overpaid loan	17	0.15	0.36	0	1
active	Acrive Loan	31	0.28	0.45	0	1
lo_1	Location 1	15	0.14	0.34	0	1
lo_2	Location 2	11	0.10	0.30	0	1
lo_3	Location 3	33	0.30	0.46	0	1
lo_4	Location 4	13	0.12	0.32	0	1
lo_5	Location 5	5	0.05	0.21	0	1
lo_6	Location 6	20	0.18	0.39	0	1
lo_7	Location 7	7	0.06	0.24	0	1
lo_8	Location 8	3	0.03	0.16	0	1
lo_other	Other Location	1	0.01	0.09	0	1
protestant	Protestant	94	0.85	0.36	0	1
catholic	Catholic	6	0.05	0.23	0	1
muslim	Muslim	8	0.07	0.26	0	1
rel_unknown	Unknown Religion	3	0.03	0.16	0	1
group	Group	7	0.06	0.24	0	1
retail_food	Business selling food	45	0.41	0.49	0	1
retail_supplies	Business selling supplies	40	0.36	0.48	0	1
animal_husb	Animal husbandry business	8	0.07	0.26	0	1
craftsman	Craftsman business	3	0.03	0.16	0	1
farming	Farming business	5	0.05	0.21	0	1
other_busi	Other business (solar oven making)	10	0.09	0.29	0	1

Table 2

OLS Regression Output Summary

Variables	Default Rate	SE
clsd_oblmet	-0.471***	0.0656
overpaid	-0.469***	0.0746
active	-0.239***	0.0693
lo_1	0.146*	0.0848
lo_2	0.0381	0.0866
lo_3	0.0733	0.0688
lo_4	0.269***	0.1020
lo_5	0.147	0.1130
lo_6	0.0639	0.0805
lo_7	-0.0566	0.1230
lo_other	-0.179	0.2010
protestant	0.0746	0.0893
Muslim	0.220**	0.1030
rel_unknown	0.180	0.1460
group	0.232***	0.0762
retail_food	-0.204**	0.0822
retail_supplies	-0.117	0.0772
craftsman	-0.171	0.1370
farming	-0.124	0.1160
other_busi	-0.169*	0.0942
Constant	0.441***	0.1440
Observations	111	
R-squared	0.696	

* $p < .10$. ** $p < .05$. *** $p < .01$.

Table 3

Y-Consistency vs. Set Value

Set	Y Consist	Set Value	F	*p*	NumBestFit
1. abde	.227	.800	239.63	< .001	75
2. abdE	.381	.800	13.53	< .001	8
4. abDe	.393	.800	5.42	.022	7
3. aBde	.516	.800	7.18	.008	8

Table 4

Conditions for a Low Default Rate

Path	Location 4	Muslim	Group Loan	Other Business
1	-	-	-	-
2	-	-	-	Yes
3	-	Yes	-	-
4	-	-	Yes	-