

Does Microcredit Reduce Household Vulnerability to Poverty? Empirical Evidence from Bangladesh

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Abstract

Household poverty is a dynamic phenomenon, and thus requires dynamic analyses rather than traditional static measurements. We argue that if we use dynamic measurements of poverty, microcredit does not reduce a household's poverty. Not only that, it may increase vulnerability to poverty for chronically poor households. These results contradict most of the existing literature that measures poverty with static methods. We analyzed our data both with static and dynamic measurements, and find the same results as the existing literature when using static measures. Thus, we argue that impact analyses of micro-credit need to incorporate the dynamic nature of poverty.

Keywords: Micro-credit; vulnerability to poverty; dynamics of poverty; FGLS

The availability of credit is important for the lives of poor rural households in the developing world. However, these households are mostly excluded from the formal banking system because they lack capital assets for collateral, and have low income levels. Micro-credit programs offer small loans to the poor to undertake projects that generate income to support themselves and their families; most of these loans do not require collateral.² The system has become a favourite of anti-poverty schemes, due in large part to its track record in the last 30 years helping the poor in countries such as Bangladesh or India.

The popularity of micro-credit programs is evident in many developing countries. In Bangladesh alone, it effectively covers some 18.1 million households without overlapping, with 62 percent of them are living below the poverty line (Microcredit Regulatory Authority, 2006).

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² Source: <http://www.grameenfoundation.com>

Academics are still debating the actual effect of micro-credit in improving the wellbeing of the poor (Montgomery and Weiss, 2005). The literature shows that micro-credit programs have either a positive or limited impact on poverty reduction (Hulme & Mosley, 1996; Zeller & Meyer, 2003; Amin, Rai, & Topa, 2001). Nevertheless, these studies measure poverty the traditional way by looking at household observed expenditures or consumption levels, which tells us little about their future poverty prospects. Given the dynamic nature of poverty, there is a need to analyze the impact of micro-credit programs on the vulnerability to poverty of the poor. Access to micro-credit programs is supposed to help the poor through two channels that are related to a household's vulnerability to poverty: income generation and consumption smoothing (Chaudhuri, Jalan, & Suryahadi, 2002). This paper proposes to assess the impact of access to micro-credit programs on a household's vulnerability to poverty through a dynamic analysis of poverty.

The objective of this study is to answer the following questions: i) Does access to micro-credit programs reduce a household's vulnerability to poverty? ii) Does this effect differ among groups of vulnerable households with different characteristics?

This paper is divided into five sections. In Section I, we give an over-review of the empirical and theoretical literature that analyzes the effect of micro-credit on poverty. In Section II, we describe the sample data used in the empirical analysis of this study. In Section III, we present the empirical models that use dynamic measurements of poverty. In Section IV, we discuss our results, and compare the dynamic model and the static models. Finally, we conclude by outlining suggestions for future research.

I. Literature Review

Commonly used measures of poverty are either based on household current income-expenditure or calorie intake. Studies on consumption patterns of poor households, especially the core-poor, indicate that the poor first spend their loan on daily consumption before investing in production (Montgomery & Weiss, 2005). As a result, it is not surprising to find access to micro-credit programs having a positive impact on poverty reduction through these common measures of poverty. Poverty remains nevertheless a dynamic problem, both theoretically and in terms of its policy importance (Chaudhuri, Jalan, & Suryahadi, 2002). The dynamic nature of poverty is that the household that is poor today may not be poor in the next period, or today's moderately poor household may become extremely poor next period.

Therefore, the traditional static approaches to measure poverty fail to capture such dynamic properties.

Various studies suggest that a dynamic approach should be used in measuring households' vulnerability to poverty (Chaudhuri, Jalan, & Suryahadi, 2002; Amin, Rai, & Topa, 2001). Vulnerability to poverty measures the *ex ante* poverty; that is, it measures who is likely to be poor and how poor they are likely to be. By definition, vulnerability assessment is forward-looking. This is particularly important for policies that are designed to have long-term effects on poverty reduction, which currently rely on a temporal measurements of poverty. Although ideally we would use panel data to estimate vulnerability at the household level, Chaudhuri et al. (2002) argue that we can achieve the same through analysis using cross-sectional data by careful selection of variables. The validity of this method stems from how differences in vulnerability to poverty among households can be attributed to variations of certain household characteristics, such as gender, age, education and main occupations of the household heads. In their proposed method, vulnerability to poverty is measured as the probability that a household's expected consumption will fall below a predetermined level.

The merits of micro-credit programs are thought to be channeled either through consumption-smoothing mechanisms and/or income generating production. In either case, having access to micro-credit programs should improve a borrowing household's ability to cope with potential shocks, thus reduce its vulnerability to poverty (Morduch, 1999).

Amin et al. (2001) showed that a poor household is more vulnerable than a richer one. However, within poor households, the cause of poverty and vulnerability may vary. Current work on the relationship between micro-credit and vulnerability to poverty is restricted to descriptive analysis of sub-groups of the population, but lacks empirical support due to data limitations (Zaman, 1999; Montgomery & Weiss, 2005). This paper contributes to the scarce empirical literature on this topic.

II. Data

One should ideally use panel data of sufficient length and richness to estimate vulnerability at the household level. However, such datasets are rare, especially for poor developing economies. Instead, we can use cross-sectional household surveys with detailed data on household characteristics such as consumption expenditures and income (Chaudhuri, Jalan, & Suryahadi, 2002). This study uses data collected from rural northern Bangladesh using the “Structured Personal Interview” method. The data is collected through stratified random sampling. The dataset includes information on rural households’ socio-economic conditions, such as income and expenditure, credit, education, land and asset holdings, as well as other community characteristics.

The data was collected from three villages in northern Bangladesh along the Surma basin.³ The villages were chosen for the intensity of poverty and availability of the both borrower and non-borrower households. The majority of households generated income from agriculture and related activities. The researchers collected data from two types of households, borrowers and non-borrowers of micro-credit. The measurement unit of the target population was the household and 110 were surveyed. Out of those, more than 60 percent were borrowing from one or more micro-credit institutions. (Table 1) All of the borrower households have been borrowing for a minimum of one year and more than 80 percent have been borrowing for more than three years. The detail household characteristics are in Table 1 of Appendix.

Table1. Distribution of Household by Borrowing Status

Category	Total
Microcredit Borrower	70
Microcredit Non-Borrower	40
Total	110

³ These three villages are: Enat Nogar, Khadirpur and Islampur. They are part of the South Sunamgonj thana of the Sunamgonj District.

III. Methodology

Our analysis consists of the following steps: estimating expected consumption, evaluating vulnerability to poverty for each household, examining the relationship between access to micro-credit programs and household vulnerability to poverty, and finally comparison of the impact of access to microcredit programs on poverty reduction between dynamic and traditional static method. In order to measure vulnerability, we use the methods developed by Chaudhuri et al (2002), where a household's vulnerability level at time t is the probability of its expected consumption level to remain below the poverty line at time $t+1$. To assess the impact of a micro-credit loan on household vulnerability to poverty, we regress the estimated vulnerability of individual household on a set of household characteristics. One of our main interests is to examine the dummy variable for access to micro-credit, and see if it has a significant effect on vulnerability to poverty.

i) Estimation of Household's Vulnerability to Poverty Using Expected Consumption

We define vulnerability as the expected poverty in the near future conditioned on a household's current characteristics. For a given household h , its vulnerability V_h at time t is the probability of the log of its expected consumption $\ln\hat{c}_h$ to be below the log of the poverty line $\ln\bar{c}$ at time $t+1$:

$$V_h = Pr(\ln\hat{c}_h < \ln\bar{c}) \quad (1)$$

In order to compare the expected consumption and the poverty line, we first estimated expected household consumption using a set of household characteristics X_h in the following form:

$$\ln c_h = X_h \beta + \varepsilon_h \quad 2)$$

where c_h stands for per capita consumption expenditure for household h ; X_h represents a set of observable household characteristics; β is a vector of parameters, and ε_h is a mean-zero disturbance term. Consumption expenditure c_h is assumed to be log normally distributed, as is the disturbance term ε_h . We also assume that the variance of log consumption varies with the values of household characteristics, X_h . This implies that the error variance of the equation (2) is assumed to be heteroscedastic.

In order to obtain an efficient estimate of $\hat{\sigma}_h$, and following Chaudhuri, Jalan and Suryahai (2002), we use the feasible generalized least square (FGLS) method to achieve a homoscedastic variance $\hat{\sigma}_h^2$. First, we saved the OLS estimated residual from equation (2) and used its square to estimate the following using another OLS procedure:

$$\hat{\varepsilon}_h^2 = X_h\theta + \eta_h \quad (3)$$

Then we use the fitted value $X_h\hat{\theta}$ to transform equation (3) as follows:

$$\frac{\hat{\varepsilon}_{h,OLS}^2}{X_h\hat{\theta}_{OLS}} = \left(\frac{X_h}{X_h\hat{\theta}_{OLS}} \right) \Gamma + \frac{\eta_h}{X_h\hat{\theta}_{OLS}} \quad (4)$$

The above transformed equation is estimated using OLS to obtain an asymptotically efficient estimate of standard error $\hat{\sigma}_h$, which is expressed as:

$$\hat{\sigma}_h = \sqrt{X_h\hat{\Gamma}} \quad (5)$$

The set of household characteristics, X_h used in the estimation of equation (2) includes the age, gender, and years of education of the household head, the size of the household, a dummy variable for the main occupation of the head of the household, dependency ratio, the size of the owned and leased land, and a dummy variable for ownership of income generating assets. Based on current literature, elderly male-headed households with higher levels of education are expected to have higher incomes; hence these households will have higher expected consumption levels. In a rural economy, such as Bangladesh, the bulk of a household's income comes from the main occupation of the household head. The dummy for the main occupation of the household-head takes on a value of one if the head works in agriculture and related industries, and zero otherwise. The dummy for ownership of income generating assets is equal to one if the household owns any, and zero otherwise.

The size of leased and owned cultivable land and possession of income generating assets are expected to be positively related to household income and consumption levels. Household size is expected to be significantly related to a household's consumption level, but the sign of the coefficient will depend on the number of earners in the household as well as income per earner.

The dependency ratio is defined as the ratio of the number of dependents to the size of the household. A higher dependency ratio is expected to lower a household's consumption level by reducing their average consumption. In addition, we expect that the age of the household head, size of the household, and land holding (both leased and owned land) will have a non-linear relationship with consumption. Therefore, the model includes the squared terms of these variables.

In order to estimate a household's vulnerability to poverty \hat{V}_h , we used the fitted value of log consumption $\ln \hat{c}_h$ and the efficient estimation of the standard error of the consumption function $\hat{\sigma}_h$ to transform equation (1) in the following way:

$$\hat{V}_h = \widehat{Pr} (\ln \hat{c}_h < \ln \bar{c} \mid X_h) = \Phi \left[\frac{\ln \bar{c} - \widehat{\beta} X_h}{\hat{\sigma}_h} \right]. \quad (6)$$

The poverty line \bar{c} is calculated based on the Cost-of-Basic-Needs (CBN) approach. According to the CBN method, a household is defined as poor if its per capita consumption expenditure lies below a certain level.⁴ The per capita expenditure of a household is the amount of money needed to buy an exogenous set of low-cost adequate food and other requirements. The function $\Phi \left[\frac{\ln \bar{c} - \widehat{\beta} X_h}{\hat{\sigma}_h} \right]$ denotes the cumulative density function of the standard normal distribution of the log consumption.

ii) Categorizing Households

Following Suryahadi and Sumarto (2003), we categorized the sample households into several groups based on their current consumption c_h , estimated expected consumption \hat{c}_h , and estimated vulnerability level \hat{V}_h .

(Table 2) Given that vulnerability to poverty is a probability, we use 0.5 as the vulnerability threshold. The existing literature supports this choice of threshold because it is where the expected log consumption coincides with the log of the poverty line (Chaudhuri, Jalan, & Suryahadi, 2002; Suryahadi & Sumarto, 2003).

⁴ Bangladesh Bureau of Statistics (BBS) 2003, "Report of The Household Income & Expenditure Survey, 2000". Bureau of Statistics, Bangladesh. The poverty line we used here is equal to 11693 Bangladesh Taka.

It is also reasonable to assume that a household is more vulnerable if it has a 50 percent or higher chance of falling into poverty in the near future.

Table 2. Categorization of Households

		Current Consumption			
		$c_h < \bar{c}^*$	$c_h \geq \bar{c}^*$		
Vulnerability to Poverty	$\hat{v}_h \geq 0.5$	A	B	$\hat{c}_h < \bar{c}$	Expected Consumption
	$\hat{v}_h < 0.5$	C	D	$\hat{c}_h \geq \bar{c}$	

Poor = **A + C**

- Chronic Poor = **A**
- Transient Poor = **C**

Non-poor = **B + D**

- High Vulnerability Non-poor = **B**
- Low Vulnerability Non-poor = **D**

High Vulnerability Group = **A + B**

Low Vulnerability Group = **D**

Total Vulnerable Group = **A + B + C**

A total of five groups of households emerge: the “poor”, the “non-poor”, the “high vulnerability group”, the “low vulnerability group”, and the “total vulnerable group”. Based on current consumption levels, the population is divided into the “poor” and the “non-poor” groups. Those households whose current consumptions are equal to or below the poverty line are the “poor”; the rest are “non-poor”. The poor households are composed of two distinct groups: the “chronic poor” and the “transient poor”. The chronic poor are households who are currently poor, have expected consumption level below the poverty line, and whose estimated vulnerability is higher than the threshold. These households are most likely to remain poor in the near future.

In contrast, the transient poor households are currently poor, but their expected consumption is above the poverty line and their vulnerability is below the threshold point. The non-poor households are also separated into two groups: the “low vulnerability non-poor” and the “high vulnerability non-poor”.

The “high vulnerability non-poor” are those household whose current consumption is greater than the poverty line but whose expected consumption is lower than the poverty line, and whose vulnerability level is above the threshold.

For the purpose of this study, we focus the analysis on the “high vulnerability” group, which consists of both the chronic poor and high vulnerability non-poor. We also examined the “total vulnerable” group, which is the combination of both the “high vulnerability” group and the transient poor.

iii) Evaluating the Impact of Micro-credit Programs on Vulnerability to Poverty

In order to study the determinants of vulnerability to poverty, we considered the following equation using the 2-stage least square method:

$$\hat{V}_h = Z_h\alpha + \mu_h \quad (7)$$

where \hat{V}_h is the estimated vulnerability to poverty from equation (6); Z_h is a combination of household characteristics used in equation (2) plus a dummy of access to micro-credit programs, which takes the value of one if the household is a borrower and zero otherwise; α is a vector of coefficients, and μ_h is the error term. The estimations are performed for two groups of the sample households, the “high vulnerability” group and the “total vulnerable” group.

In this model, the variable “access to micro-credit” is assumed to be correlated with some household’s characteristics that are not included in our model. In order to solve the endogeneity problem, we used the dependency ratio as an instrumental variable (IV). The theoretical justification for using dependency ratio is that a household with more dependents is more likely to borrow microcredit due to financial needs. We used a Probit regression to determine the relationship between the dependency ratio and access to micro-credit. We found that the dependency ratio is not statistically significantly related with vulnerability to poverty but it significantly determines if a household is a borrower of micro-credit.

iv) Static and Dynamic Approach

The static model measures poverty using current consumption levels. In order to compare our results with the static model, we estimate the following equation:

$$Poverty = K_h \delta + \epsilon_h \quad (8)$$

$$Poverty = \begin{cases} 1 & \text{if } poor \\ 0 & \text{if } non - poor \end{cases}$$

where K_h is some combination of household characteristics⁵ plus a dummy variable for access to micro-credit, as in equation (7). A household is defined as poor if its current consumption levels lie below the poverty line, and as non-poor otherwise. Because the dependent variable is a dummy, an IV-Probit model is used to estimate equation (8). The dependency ratio is used as the IV in this case as well. The purpose for this comparison is to demonstrate how the impact of access to micro-credit on poverty reduction differs depending on how one measures poverty.

IV. Results and Discussion

Based on the grouping scheme of households illustrated in the previous section, we found that 70 out of 110 households took micro-credit loans. About half of the borrowers are “high vulnerability” households, and more than half of the 40 non-borrowers are highly vulnerable. Non-borrowers have a larger proportion of households belonging to the “total vulnerable” and “high vulnerability” groups; however we found the proportion differences between borrowers and non-borrowers to be statistically insignificant after using the Proportion test. (Table 3) This indicates that the proportional differences between borrowers and non-borrowers may stem from differences in sample size, and is not due to differences in household characteristics.

⁵ K_H excludes these variables from Z_h : gender of the household head, and income generating asset dummy.

Table 3: Summary Statistics of the Categorization of Households and Proportion test

	Borrowers¹	Non-borrowers²	Proportion Test p-value
Total Vulnerable Households	64%	75%	0.88
High Vulnerability	49%	55%	0.31
Low Vulnerability	51%	45%	0.78
Total	100%	100%	-

¹ In total, 70 household are borrowers of micro-credit.

² In total, 40 households are non-borrower of micro-credit.

Based on the regression using a dynamic measurement of poverty, we found that being a borrower of micro-credit does not increase a household's vulnerability to poverty for the "total vulnerable" group. The coefficient estimation of the borrower dummy variable is positive, but statistically insignificant. Meanwhile, age, gender, years of schooling and main occupation of the household head are significant determinants of a household's vulnerability to poverty. A household's vulnerability to poverty is lower if the head is an elderly male. With increasing years of education of the head of the household, the household's vulnerability to poverty decreases. The size of leased land and ownership of income generating assets are also positively related to reduction of a household's vulnerability to poverty. We did not find land ownership to be a determinant of vulnerability to poverty since the majority of households in our sample own limited amounts of cultivable land and cannot reach a profitable production scale. Azam and Imai (2009) found that chronic poverty is widespread among households whose main income relies on agricultural production. Our findings support this claim; if the head of a household works in agriculture and related industries, the household will be more vulnerable to poverty than if their main income came from non-agricultural activities. The regression results for this group are presented in Table 2 of the Appendix.

When comparing dynamic and static measurements of poverty (vulnerability to poverty), the results tell a conflicting story.

We found that being a borrower of micro-credit significantly reduces a household's poverty level, as measured by their current consumption. In fact, taking a micro-credit loan is the most deterministic factor in reducing poverty. In their survey of empirical studies on the effectiveness of micro-credit, Montgomery and Weiss (2005) found that micro-credit almost always has a positive poverty reduction effect on poor households if one measures poverty using current consumption. The static model regression results for the "total vulnerable" group are in the Table 3 of the Appendix.

We found that borrowing micro-credit will increase vulnerability to poverty for the "high vulnerability" group, and this relationship is statistically significant. This result is noteworthy, especially given that the static model shows that for this group of households, taking micro-credit loans should reduce their poverty levels significantly. For the "high vulnerability" group, we found that a female headed household will have lower vulnerability to poverty than a male-headed household. Other determinants of vulnerability are found to have a similar relationship as the findings for the "total vulnerable" group. The dynamic and static model regression results for this group of households are presented in the Table 4 and 5 of the Appendix.

The differences in household characteristics between the two focus groups may explain why micro-credit increases the vulnerability for one group while it has no effect on the other. Within the "total vulnerable" group, we found that a large proportion of households are transiently poor. These households are on their way to escape poverty. Although their current consumption levels are below the poverty line, their predictable consumption in the near future is going to be above it, and thus have lower vulnerability to poverty. On the contrary, within the highly vulnerable group, there are relatively larger proportions of households who are chronically poor. These households are likely to remain in poverty in the future, due to their low consumption levels now and in the near future. Subsequently, if these chronically poor households choose to take micro-credit loans, their priorities will be to increase spending on consumption to meet their basic needs. As a result, it is unlikely that they will invest in income generating production activities, especially given that the size of the credit is usually small. Hence, this group of households will be more vulnerable to poverty.

Although one of the merits of micro-credit is to smoothen consumption patterns for the poor, such an effect can only relax the squeeze of poverty temporarily. In the long-term, the poor need to increase their income to break away from the cycle of poverty.

Within our sample of 70 borrower households, 44 percent of them reported that they borrowed to increase current consumption and only 33 percent indicated that the purpose of borrowing is to use the loan to generate additional income. Furthermore, only 16 percent of the borrower households were able to generate new self-employment through micro-credit. Researchers have shown that the success of NGO-led micro credit programs depends critically on monitoring how loans are allocated. Without monitoring, poor households do not always have the knowledge or skills to improve their wellbeing by making the right investment choices. However, we found that within our sample, 75 percent of borrowers had no guidance from the issuing agencies.

V. Conclusion

Although arguably a helpful and important mechanism in the fight against chronic poverty, micro-credit falls short from being a miraculous cure. In this study we found that having access to micro-credit leads to an increase in vulnerability to poverty, especially for the groups of households that consisted of the more chronically poor. Poverty is a complex issue, and it is crucial to measure it appropriately when evaluating the effectiveness of micro-credit. As we have demonstrated, static measurements of poverty based on current consumption expenditures can lead to deceptive results. These measurements do not incorporate a household's future state of poverty, and therefore fail to fully evaluate how effective micro-credit programs are in reducing poverty. Our findings show that we do not have the evidence to convincingly argue that micro-credit contributes to reductions in poverty.

Bibliography

- Amin, S., Rai, A. S., & Topa, G. (2001). Does Microcredit Reach the Poor and Vulnerable? Evidence from Northern Bangladesh. CID Working Paper NO.28, Center for International Development at Harvard University.
- Azam, M. S., & Imai, K. S. (2009). Vulnerability and Poverty in Bangladesh. ASARC Working Papers, Australian National University, Australia South Asia Research Centre.
- Chaudhuri, S., Jalan, J., & Suryahadi, A. (2002). Assessing Household Vulnerability to Poverty from Cross-Sectional Data: A Methodology and Estimates from Indonesia. Discussion Paper #0102-52, Columbia University, Department of Economics .
- Hulme, D., & Mosley, P. (1996). *Finance Against Poverty* (Vol. 1 and 2). London: Routledge.
- Kamanou, G., & Morduch, J. (2005). Measuring Vulnerability to Poverty. In S. Dercon (Ed.), *Insurance Against Poverty* (pp. 156-175). New York: Oxford University Press.

- Microcredit Regulatory Authority. (2006, June). NGO-MFIs in Bangladesh. Retrieved April 9th, 2011, from Bangladesh Bank: <http://www.bangladesh-bank.org/pub/annual/mrru/ngomfisbd.html>
- Montgomery, H., & Weiss, J. (2005). Great Expectations: Microfinance and Poverty Reduction in Asia and Latin America. ADB Institute. ADB Institute.
- Morduch, J. (1999). The Microfinance Promise. *Journal of Economic Literature* , XXXVII, 1569-1614.
- Suryahadi, A., & Sumarto, S. (2003). Measuring Vulnerability to Poverty in Indonesia Before and After the Economic Crisis. *Asian Economic Journal* , 17 (1), 45-64.
- Zaman, H. (1999). Accessing the Poverty and Vulnerability Impact of Micro-Credit in Bangladesh: A case study of BRAC. The World Bank, The Chief Economist and Senior Vice-President (DECVP) .
- Zeller, M., & Meyer, R. L. (Eds.). (2003). *The Triangle of Microfinance: Financial Sustainability, Outreach and Impact* . Johns Hopkins University Press .

Appendix

Table 1. Summary Statistics for Explanatory Variables

Variables	Mean	Stander Deviation
Household per capita expenditure	12120.6	4148.1
Age of the household-head	40.1	11.9
Household size	6.0	2.2
Education of the household-head (years of schooling)	0.8	1.4
Dependency Ratio	0.8	0.1
Leased Land	2.6	7.4
Owned cultivable land	1.4	4.0

Variables	Category	Frequency	Percentage
Dummy, Income Generating Asset	Yes	54.0	49.1
	NO	56.0	50.9
Dummy, Main occupation of the household-head	Agricultural	78.0	70.9
	Non-Agricultural	32.0	29.1
Dummy, Gender of the household-head	Male	96.0	87.3
	Female	14	12.7

Table 2. Regression Result for Determinants of Vulnerability, the Total Vulnerable Group

Number of observation=75

Wald chi2(13) = 616.53

Prob > chi2=0.00

R-squared=0.885

Root MSE=0.095

Vulnerability	Coef.	Std. Err.	Z	P> z
Dummy, Borrower	0.138	0.110	1.250	0.210
Age of Head of Household	-0.100	0.007	-14.870	0.000
Age ²	0.001	0.000	12.830	0.000
Gender of Head of Household	0.121	0.047	2.600	0.009
Household Size	0.060	0.032	1.850	0.065
Household Size ²	0.003	0.002	1.100	0.271
Years of education of Head of Household	-0.091	0.011	-8.610	0.000
Main Occupation of Head of Household	-0.345	0.027	-12.630	0.000
Leased land	0.037	0.008	4.900	0.000
Leasedland ²	-0.001	0.000	-5.420	0.000
Owned Cultivable land	0.022	0.019	1.200	0.229
Owned Cultivable land ²	-0.001	0.001	-1.170	0.240
Dummy, Income Generating Assets	0.146	0.029	5.100	0.000
Constant	2.331	0.145	16.080	0.000

Table 3. Static Model, the Total Vulnerable Group

Number of Observations=68

Wld Chi2(11) =94.42

Prob>chi2=0.00

Log likelihood=-48.56

Poverty	Coef.	Std. Err.	z	P> z
Dummy, Borrower	-2.406	0.256	-9.410	0.000
Age of Head of Household	0.151	0.095	1.590	0.112
Age ²	-0.002	0.001	-1.640	0.100
Household Size	-0.621	0.629	-0.990	0.323
Household Size ²	0.060	0.053	1.130	0.258
Years of education of Head of Household	0.147	0.125	1.180	0.240
Main Occupation of Head of Household	0.251	0.348	0.720	0.471
Leased land	-0.158	0.079	-1.990	0.046
Leasedland ²	0.006	0.004	1.550	0.121
Owned Cultivable land	-0.411	0.153	-2.690	0.007
Owned Cultivable land ²	0.023	0.014	1.680	0.094
Constant	0.219	1.829	0.120	0.905

Table 4. Regression Result for Determinants of Vulnerability, the High Vulnerability group

Number of observations =55

Wald chi2(13) =628.54

Prob > chi2 = 0.00

R-squared = 0.92

Root MSE = 0.04

Vulnerability	Coef.	Std. Err.	z	P> z
Dummy, Borrower	0.080	0.039	2.040	0.042
Age of Head of Household	-0.106	0.006	-18.740	0.000
Age ²	0.001	0.000	18.010	0.000
Gender of Head of Household	-0.044	0.033	-1.340	0.180
Household Size	0.150	0.025	6.010	0.000
Household Size ²	-0.003	0.002	-1.620	0.105
Years of education of Head of Household	-0.099	0.007	-14.860	0.000
Main Occupation of Head of Household	-0.347	0.021	-16.340	0.000
Leased land	0.031	0.005	6.820	0.000
Leasedland ²	-0.001	0.000	-6.180	0.000
Owned Cultivable land	0.016	0.008	2.040	0.042
Owned Cultivable land ²	-0.001	0.001	-1.400	0.162
Dummy, Income Generating Assets	0.104	0.019	5.570	0.000
Constant	2.409	0.117	20.510	0.000

Table 5. Static Model, the High Vulnerability group

Number of observation= 55

Wald chi2(11) =37.79

Prob > chi2 =0.0001

Log likelihood = -37.793001

Poverty	Coef.	Std.	Err.	z	P> z
Dummy, Borrower	-2.335	0.522	-4.480	0.000	-3.358
Age of Head of Household	0.117	0.146	0.800	0.423	-0.169
Age ²	-0.001	0.002	-0.650	0.513	-0.004
Household Size	0.020	1.088	0.020	0.985	-2.112
Household Size ²	0.034	0.092	0.380	0.707	-0.145
Years of education of Head of Household	0.265	0.238	1.120	0.265	-0.201
Main Occupation of Head of Household	0.065	0.498	0.130	0.897	-0.912
Leased land	-0.190	0.172	-1.110	0.269	-0.527
Leasedland ²	0.007	0.010	0.740	0.459	-0.012
Owned Cultivable land	-0.316	0.281	-1.120	0.261	-0.866
Owned Cultivable land ²	0.007	0.026	0.250	0.799	-0.044
Constant	-1.945	3.234	-0.600	0.548	-8.285