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# Does Microcredit Reach the Poor and Vulnerable? Evidence from Northern Bangladesh

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## Abstract

Subsidized loans have a history of being diverted to the rich. Yet recently microcredit programs, such as the Grameen Bank in Bangladesh, have become popular among donors and governments as a way to channel funds to the poor. This paper uses a unique panel dataset from two Bangladeshi villages to test if the modern microcredit movement is different from its predecessors. Poverty is measured by levels of consumption. Vulnerability is measured as fluctuations in consumption associated with inefficient risk sharing. We find that subsidized credit is largely successful at reaching the poor and vulnerable. The probability that a microcredit member is below the poverty line is substantially higher than that of a randomly picked household in both villages. In the village where female headed households were found to be vulnerable, nearly half of the female headed households belonged to microcredit programs yet only a quarter of male headed households were microcredit members. While restricting loans to the landless is not effective in reaching the poor and vulnerable, targeting female headed households is.

**JEL Codes**: O16, I38, Q12

**Keywords**: poverty, vulnerability, microcredit, targeting, Grameen Bank

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# 1 Introduction

There is a long and disappointing history of subsidized credit intended for the poor being politically manipulated and diverted to the rich and powerful. For instance, 80% of the $56 million subsidies provided to Costa Rica's largest bank in 1974 went to large wealthy farmers (Vogel [26]). A Latin American rural financial institution received $10.3 billion in capital injections and interest subsidies in the 1980's but served only 2 percent of the rural population and recovered only $10-15$ percent of its loans (Yaron et al. [29]). Critics of subsidized credit allege that the lower the real interest rate, the more heavily concentrated the loans will be in favor of rich (Adams et al [1]).

Yet recently microcredit has become "the world's hot idea for reducing poverty (New York Times [15])." A high profile consortium of policymakers, donors and practitioners pledged in 1997 to raise $20 billion over 10 years for microcredit programs (Microcredit Summit Report [11]). The Grameen Bank in Bangladesh, a subsidized credit provider, is seen as the flagship for this anti-poverty movement. The Grameen Bank targets the landless, restricts its loans to women, and claims to reach the poorest and most vulnerable.[1] This claim has never been tested before, however.

We use a unique data set from two villages in Northern Bangladesh to show that microcredit programs including Grameen are successful at reaching the poor and vulnerable.[2] The probability that a microcredit member is below the poverty line is substantially higher than that of a randomly picked household in both villages. In the village where female headed households were found to be vulnerable, nearly half of the female headed households belonged to microcredit programs yet only a quarter of male headed households were microcredit members. Thus, we provide evidence that the modern microcredit movement is different, at least in this respect, from the failed attempts at subsidized credit in the past. Our results are surprising because many economists believe that poor and vulnerable households are high risk and therefore likely to be credit constrained. We also find that targeting

[1] On average, Grameen has an adjusted repayment rate of 92%, a real interest rate of 10%, and a subsidy of 11 cents per dollar lent for the period $1985-1996$ (see Morduch [12])

[2] The programs we consider are the Grameen Bank, Bangladesh Rural Advancement Committee (BRAC) and Association for Social Advancement (ASA). BRAC and ASA use group lending schemes similar to Grameen's.

loans to the landless, an eligibility requirement that is not enforced in practice, is not an effective way to reach the poor and vulnerable. Anti-poverty credit programs in Bangladesh should look beyond the landless to female headed households as a possible target group.

We define poverty in terms of levels of consumption, and vulnerability in terms of fluctuations associated with imperfect risk sharing. Vulnerable households are those that are unable to smooth consumption in the face of fluctuations of income due to crop disease, floods, illness, and other idiosyncratic shocks to household resources. We use consumption and income data for 229 households for twelve months in $1991-92$ to identify those that are poor and vulnerable. Then we check which of these households joined a microcredit program by 1995. Since microcredit organizations only just began to give loans in the two villages in $1991-92$, we can ignore issues of endogeneity for the most part.

While there has been some research on microcredit's *impact* on the welfare of participating households in Bangladesh (Pitt and Khandker [17] and Morduch [13]), this paper empirically addresses *selection* into microcredit programs.[3] Further, as far as we know, this is the first paper to explicitly evaluate the targeting of an intervention using the general equilibrium notion of efficient risk sharing.[4] In addition to the obvious equity motives, there are efficiency reasons to target the vulnerable. Vulnerable households are excluded from risk sharing networks in the village. Microcredit programs may be correcting for inefficiencies in institutions and markets by providing them credit with contingencies (Rashid and Townsend [19]). For instance, Grameen Bank's design comprises several insurance funds that provide repeat loans during hard times (Shams [23]).

The rest of the paper is organized as follows. Section 2 describes the two villages and the data. Section 3 derives a measure of vulnerability and describes its estimation. Section 4 associates poverty and vulnerability with household characteristics. Section 5 reports our findings on whether microcredit reaches the poor and vulnerable. Alternative targeting strategies are discussed in Section 6. Section 7 concludes.

[3] The only other empirical study we know of that tests whether microcredit reaches the poor is Navajas et al. [14]. They find that five microfinance programs in Bolivia typically reach "the richest of the poor." Since their data were collected after households had joined microfinance programs, they are not able to control for endogeneity bias.

[4] There have been several tests of efficient risk sharing in village economies (see Townsend [24], Ligon [9], and Ravallion and Chaudhuri [20], among others).

## 2 Data and Setting

The study uses transactions data collected over 12 months in two villages (called $A$ and $B$ to preserve anonymity) in the district of Rajshahi in north-west Bangladesh. Table 1 reports the distribution of occupations within each village. Village $A$ is primarily agricultural while village $B$ is more diversified in its income sources: only 20% of the households in village $A$ but over half the households in village $B$ do not report agriculture or daily labor as their main occupation. In $B$, substantial shares are employed in trading, government and NGO service, local transport, medical and other skilled services.[5] Village $B$ is 9 miles from Rajshahi city on a well travelled highway connecting Rajshahi city to Naogaon. Village $A$ is 15 miles from Rajshahi town, and is set back 1.6 miles away from the highway. A handful of men commute from village $B$ to Rajshahi, but none from village $A$ do so. Village $B$ has several small shops, a marketplace (*haat*) that meets twice a week and attracts 200 vendors, local government offices, and a concrete mosque outfitted with a loudspeaker for calls to prayer. All major marketing activities for village $A$ are held in outside marketplaces. Consequently village $B$ is more integrated into a cash economy than village $A$. Dwellings in both villages are built on high ground. Village $A$ is surrounded by three *beels:* land depressions that remain submerged most of the year, where rice is grown. The land around village $B$ is of higher elevation making it less prone to floods. Besides three rice crops a year, village $A$ grows betel leaf, an important cash crop and village $B$ has several jointly owned mango orchards.

In 1991, there were 395 and 398 households respectively in the two villages. Of these, 120 households were sampled in each village. Male headed households had a $\frac{1}{4}$ chance of being surveyed, while all female headed households were sampled. The lack of complete data for a few households brought the number of units in our sample down to 112 for village $A$ and 117 for village $B$.

Households were followed for 12 rounds and data on income, expenditure, asset transactions, time use, loans and gifts were collected.[6] Each round corresponds roughly to a calendar month, with rounds starting in September

[5] For more on these villages, the setting and household structure see Amin [2].

[6] Resident research teams of 2 male and 2 female interviewers who were recent university graduates lived in each village between June 1991 and November 1992. The principal investigator spent approximately one week every month in the villages to supervise and participate in data collection.

1991 for village $A$ and October 1991 for village $B$. The data were collected during 20 days of the month. The data collection team was instructed not to visit the same household with anything less than a 28 day interval between visits.

Two consumption measures were created for each of the sampled households over the 12 months: food consumption and all consumption. Food consumption includes consumption from own produce of wheat and rice, purchased wheat and rice, other food purchases (e.g. vegetables and pulses), other food consumption from own produce, net meals received as wages or gifts. All consumption adds expenditure on services and other non-durable purchases (e.g. tobacco and medicines).

Measures of household income and revenue were also created.[7] All income includes net profits from own crop production, net wages earned, net profits from trading, self employment and business activities, and rent. Incomes sometimes take negative values. This is no accident: households may hire labor or buy inputs in the planting season and these will show up as negative incomes. Revenue, by contrast, comprises gross profits and wages earned and is always non-negative.

Neither consumption nor income measures include net borrowing and savings, net gifts received or net changes in asset positions (e.g. livestock). Each of these are smoothing devices used to augment consumption when incomes are low or to put aside resources when incomes are high. Field observation and the detailed transactions data indicate that zero nominal interest loans were common within both villages, and gift exchange in the form of meals or food was widespread. Table 2 reports summary statistics for the two villages. The unit of observation is a household. Village $B$ is wealthier than village $A$: average monthly consumption, income, and revenues are all higher in $B$. The average annual income is approximately \$111 in village $A$ and \$138 in village $B$. The daily agricultural wage in both villages in $1991-92$ was 20 taka plus two meals (valued at about 7 taka each) So a day's agricultural work was worth approximately \$1. Incomes and revenues are more volatile in $B$ than in $A$. Since the coefficient of variation of consumption is lower

[7] Consumption, income and revenue are in per adult equivalent terms throughout the paper. The following age-sex weights were used: 1.0 for adult males, 0.9 for adult females, 0.94 for males aged $13-18$, 0.83 for females aged $13-18$, 0.67 for children aged $7-12$, 0.52 for children aged $4-6$, 0.32 for toddlers aged $1-3$, and 0.05 for infants. These weights are the same as those used by Townsend [24] which are based on a south Indian dietary survey.

than that of income or revenues for both villages, there appears to be some consumption smoothing by households.

Wodon [28] calculates a poverty line of 425 taka annual consumption for Rajshahi for $1991-92$ using the cost of basic needs method.[8] According to his estimates, 62% of rural Rajshahi and 47% of rural Bangladesh is below the poverty line. Village $A$ is poorer than the average Rajshahi village: 68% of the sampled households are below the poverty line. On the other hand, village $B$ is slightly richer than the average Rajshahi village but still poor relative to the national average: 54% of its sampled households are below the poverty line.[9]

Figures 1 through 3 plot the deviations from average for incomes, revenues and consumptions across the 12 rounds for all sampled households in both villages. Household consumptions are generally smoother than incomes or revenues over the 12 months of the survey. Figures 1 and 2 show that there is considerable idiosyncratic (and hence diversifiable) risk in this economy. It is not the case that incomes and revenue comove across households.

A resurvey of both these villages was carried out in 1995. In particular, we have information on the number of households (or their splits) that had joined Grameen, BRAC and ASA by 1995.[10] This is the unique feature of the data that we exploit in our analysis. In $1991-92$, when the first survey was conducted, Grameen Bank had only begun to establish their presence in the two villages. In village $A$, 5 sampled households took their first loans from Grameen before the end of the survey in 1992, of which 2 took loans in the last two months of the survey. In village $B$, 14 sampled households took Grameen loans before the end of the survey in 1992, of which 4 households took loans in the last quarter of the survey.[11] By 1995, Grameen, BRAC and ASA had firmly established themselves. Throughout this paper, consumption

[8] The poverty line was set by computing the (district specific) cost of a food basket that enabled households to meet the normative nutritional requirement of 2.5 kilocalories, and adding to this an estimated allowance for non-food consumption.

[9] The percentages of households below the poverty line have been weighted to reflect the oversampling of female-headed households.

[10] Households that split between 1992 and 1995 were treated as a single unit. Field observations suggest that split households maintain very close social and economic ties, and appear to act as a single large unit.

[11] This timing problem may generate some bias in our analysis, since for those households that had already joined Grameen before the end of the survey we may estimate poverty and vulnerability levels that are affected by the loans taken from Grameen. We discuss the likely direction of such bias, wherever applicable, in Section 5.

and income data (and therefore our measures of vulnerability), as well as household categories such as female headship or landlessness are based on the $1991-92$ data. Microcredit membership data, on the other hand, are derived from the 1995 resurvey.

Table 3 summarizes the village composition in terms of several household categories (landlessness, female headship, education level of the household head) that will be used in what follows. In addition, the number of households with at least one microcredit member by 1995 is reported. About one third of all sampled households in each village had joined a microcredit program by this time. Grameen membership had gone up to 10 sampled households in village $A$ and 17 sampled households in village $B$, and total microcredit membership was 38 sampled households in each village.

Table 4 examines the differences in terms of average consumption and income levels within household categories. Landless and female headed households, as well as households with uneducated heads, are consistently poorer than their counterparts (households with more than half an acre of land, with a male head and with an educated head) in both villages. In addition, microcredit members have lower levels of average consumption and income than non members, only slightly in village $A$, and more substantially in village $B$.

Finally, it is worth mentioning that the practice of *purdah*, a set of norms that promotes the seclusion of women and excludes them from public places, remains a dominant force in these villages (Amin [3]). Female headed households are most affected by the restrictions that *purdah* imposes on their participation in the labor market, on setting up microenterprises and on the sale of produce in the market. The vast majority of the female headed households in our villages (79% in $A$ and 74% in $B$) have no sons over the age of 15, and are dependent on somebody outside their household to access the market. Furthermore, 21% of the female headed households in village $A$ and 32% of those in village $B$ are divorcees. Because of the social stigma attached to divorce, this status is likely to exclude such households further from any solidarity and insurance networks within the villages.

# 3 Estimating vulnerability

In this section we derive a measure of vulnerability and describe how we estimate household specific vulnerability parameters.[12] A household is vul-

[12] Jalan and Ravallion [8] use a similar measure.

nerable if idiosyncratic income shocks are passed on to current consumption. Our estimation strategy includes specifications for different utility functions, varying degrees of risk aversion across groups and attempts to control for unobservable preference shocks. Households that are able to fully insure themselves against idiosyncratic risk are not considered vulnerable. This definition of vulnerability is quite different from measures of consumption *variability* used by Morduch [13] and Pitt and Khandker [18] (e.g. the coefficient of variation of consumption, the variance of log consumption, or the proportion of consumption that a household would be willing to forego to achieve its certainty equivalent). A household may have highly variable consumption because it is less risk averse than others in the village. Therefore, measures of consumption variability do not give an accurate sense of how vulnerable households are.

## 3.1 Theoretical derivation

A long literature starting with Diamond [6] and Wilson [27] has established properties of an efficient allocation of risk-bearing in a general equilibrium framework. These results abstract from the specific mechanisms that can be used to smooth out consumption in the face of idiosyncratic risk,[13] and focus on the properties of the resulting allocations. Such optimal allocations are found as a solution to a social planner's problem. Under certain assumptions, (separability of consumption and leisure, common rates of time preference, additively separable preferences over time) efficient risk sharing within a village implies that household consumption should move only with aggregate consumption and not with household income. In this Section we derive this implication of Pareto efficiency and define the regression specification that we use to estimate vulnerability parameters for each household.[14]

Consider an economy with $N$ households who live for $T$ periods. At each date $t$ uncertainty is represented by a vector $\theta_t$ of shocks. Components of $\theta$

[13] An incomplete list includes storage, sale and purchase of various assets, borrowing and lending and gift exchange. The following papers, among others, have analyzed specific risk sharing mechanisms. Rosenzweig and Stark [21] and Paulson [16] study the role of migration in consumption smoothing. Rosenzweig and Wolpin [22] analyze bullock purchases and sales as a smoothing device. Udry [25] studies how informal credit serves as insurance. Lim and Townsend [10] analyze the role of buffer stocks of currency and crop inventory, informal credit and the sale of assets and livestock in bridging the gap between income and consumption.

[14] This section builds on Deaton [5], pages $372-383$, and Townsend [24].

will include weather shocks (such as floods or droughts), sickness, crop disease, and changes in prices. At any date $t$, a history of shocks is given by $s_t = (\theta_1, \theta_2 ... \theta_t)$. For each household $h$, let $c^h(s_t)$ and $l^h(s_t)$ denote consumption and leisure given a particular history.

To achieve a Pareto-optimal allocation of resources and risk, a hypothetical planner maximizes a weighted sum of utilities across households:

$$\sum_{h=1}^{N} \lambda^h \sum_{t=1}^{T} \beta^{t-1} \sum_{s_t} prob(s_t) \cdot u^h(c^h(s_t), l^h(s_t)) \tag{1}$$

subject to resource constraints for each history $s_t$:

$$\sum_h c^h(s_t) \leq C(s_t) \tag{2}$$

$$\sum_h l^h(s_t) \leq L(s_t) \tag{3}$$

where $C(s_t)$ and $L(s_t)$ denote aggregate consumption and leisure in the village contingent on the history $s_t$. The $\lambda^h$ parameters in equation (1) denote the Pareto weights attached to each household $h$.[15] The maximization is also subject to feasibility constraints on consumption and leisure for all $h$ and for all $s_t$,

$$\begin{aligned} c^h(s_t) &\geq 0 \\ 0 &\leq l^h(s_t) \leq T(s_t) \end{aligned}$$

and subject to balance of payments condition for the village as a whole: aggregate production plus net borrowing, net increase in aggregate storage, and net sales of assets to outsiders must exceed aggregate consumption at each history $s_t$.

First order conditions for this problem equate weighted marginal utilities across agents. In particular, if agents' preferences are separable across consumption and leisure, one obtains for all households $h$ and for all states $s_t$ (after taking logarithms):

$$\ln \mu^h(c^h(s_t)) = \ln \xi(s_t) - \ln \lambda^h - (t-1) \ln \beta - \ln(prob(s_t)) \tag{4}$$

[15] By varying the Pareto weights one can trace the whole Pareto frontier. These weights reflect the households' wealth, and are assumed to be time-invariant.

where $\mu^h(\cdot)$ denotes the marginal utility of consumption and $\xi(s_t)$ is the multiplier associated with equation (2).[16] Taking first differences over time allows us to eliminate the term involving the Pareto weight $\lambda^h$. For all households $h$ and for all states $s_t$:

$$\Delta \ln \mu^h(c^h(s_t)) = \Delta \ln \xi(s_t) - \Delta \ln(prob(s_t)) - \ln \beta \equiv \kappa(s_t) \quad (5)$$

Therefore, a key feature of an optimal allocation of risk within the village is that changes in log marginal utility of consumption have to be equated across households, for every history $s_t$. Let us now specialize our analysis to a constant absolute risk aversion (CARA) utility function:[17]

$$u^h\left(c^h(s_t), l^h(s_t)\right) = -\frac{1}{\zeta_t^h} n^h(s_t) \left[\exp\left(-\sigma \frac{c^h(s_t)}{n^h(s_t)}\right) + \exp(-\sigma \frac{l^h(s_t)}{n^h(s_t)})\right], \quad (6)$$

where $n^h(s_t)$ is the (age-sex adjusted) number of male adult equivalents in the household at time $t$, $\zeta_t^h$ is a preference shock and $\sigma$ is the coefficient of absolute risk aversion. Equation (5) then specializes to the following for all households $h$:[18]

$$\Delta\left(\frac{c_t^h}{n_t^h}\right) = -\frac{1}{\sigma}\kappa_t - \frac{1}{\sigma} \triangle \ln \zeta_t^h \quad (7)$$

This implies that consumption across agents should comove (modulo variations due to preference shocks), and that changes in a household's consumption should not be affected by changes in that household's income.

Equation (7) constitutes the basis of our estimation strategy. If full risk-sharing is in place and preference shocks can be treated as mean zero error terms that are uncorrelated with changes in income and with time dummies, then changes in per-adult-equivalent consumption over time should comove across households.[19] Household consumption should only be affected by aggregate fluctuations in the village, and not by idiosyncratic shocks to the household's own income or resources. Our estimation strategy focuses on

[16] We just focus on consumption. The implications for leisure comovement are similar.

[17] The implication that household consumptions should comove holds generally if agents are strictly risk averse.

[18] We drop the $s_t$ notation and use a time subscript only, as the sharing rule 5 holds for every history and therefore also for the realized sequence of shocks.

[19] In the estimation, we also examine model specifications that include direct proxies for household preference shocks.

identifying individual households within each village that are vulnerable to idiosyncratic risk.

So far we have restricted all agents to have the same coefficient of absolute risk aversion $\sigma$. If instead some agents were more or less risk averse than others, with $\sigma^h$ denoting household $h'$s degree of risk aversion, then equation (7) would become:

$$\Delta\left(\frac{c_t^h}{n_t^h}\right) = -\frac{1}{\sigma^h}\kappa_t - \frac{1}{\sigma^h} \bigtriangleup \ln \zeta_t^h \tag{8}$$

This implies again that consumptions across agents should comove, and changes in a households consumption should not be affected by changes in that household's income if risk sharing holds within the village.

In what follows we also estimate vulnerability parameters using a constant relative risk aversion (CRRA) utility specification, to ensure that our results are robust to the choice of functional form. Using the following utility function:

$$u^h\left(c^h(s_t), l^h(s_t)\right) = \frac{1}{1-\gamma}\zeta_t^h n^h(s_t)\left[\left(\frac{c^h(s_t)}{n^h(s_t)}\right)^{1-\gamma} + \left(\frac{l^h(s_t)}{n^h(s_t)}\right)^{1-\gamma}\right], \tag{9}$$

we derive the counterpart to equation (7):

$$\Delta \ln\left(\frac{c_t^h}{n_t^h}\right) = -\frac{1}{\gamma}\kappa_t - \frac{1}{\gamma}\Delta \ln \zeta_t^h \tag{10}$$

Finally, we would like to consider the possibility of economies of scale within the household. So far we have implicitly assumed that the household utility stays the same if one doubles both the total consumption in the household and the number of adult equivalents. However, it may be the case that a bigger household is more efficient and experiences increasing returns to size. Incorporating this into the analysis implies that there is an additional term in $n_t^h$ in equation (7) and (10). However, as long as the size of the household remains constant during the period under consideration, this term drops out due to the first-differencing. In our data, only 3 households in village $A$ and 2 in village $B$ change composition during the 12 months of the sample: therefore, we can safely ignore this issue.

## 3.2 Estimation strategy

In this Section, we estimate a linear regression model based on equation (7), aimed at identifying vulnerable households.

If we treat the $\zeta_t^h$ preference shocks as mean zero error terms that are uncorrelated with the other regressors, equation (7) suggests the following regression equation:

$$\Delta \widetilde{c}_t^h = \alpha^h \Delta \widetilde{y}_t^h + \phi_t \cdot MD_t + \varepsilon_t^h. \tag{11}$$

where $\widetilde{c}_t^h \equiv c_t^h / n_t^h$ denotes per-adult-male equivalent consumption of household $h$ in month $t$, $\widetilde{y}_t^h$ is (per-adult-equivalent) household income at time $t$, and $MD_t$ is a month dummy, that equals one for observations at time $t$, zero otherwise. The coefficient $\phi_t$ captures $\frac{1}{\sigma}\kappa_t$ from equation (7), which is proportional to a measure of the aggregate resource constraint at date $t$. The error term $\varepsilon_t^h$ is assumed to be uncorrelated with the RHS variables and to be mean zero. As for the covariance structure, we assume the following:

1. $\tau_{ht}^2 \equiv Var(\varepsilon_t^h) = \tau_h^2 \;\; \forall\, t$;
2. $\tau_{h,ts} \equiv Cov(\varepsilon_t^h, \varepsilon_s^h) = 0 \;\; \forall\, t \neq s$;
3. $\tau_{hk,ts} \equiv Cov(\varepsilon_t^h, \varepsilon_s^k) = 0 \;\; \forall\, h \neq k,\, t \neq s$;
4. $\tau_{hk,tt} \equiv Cov(\varepsilon_t^h, \varepsilon_t^k) = 0 \;\; \forall\, t, h, k$.

The first assumption on heteroskedasticity is motivated by the results of several tests[20] that suggest this may be an important factor. Intuitively, it seems reasonable to allow the variance of the residuals to vary across households, since they have very different sizes, landholdings, consumption and income levels. As for the other assumptions, they are quite standard. We have tested for the presence of contemporaneous correlation across households using a variety of methods, and we find very little evidence, if any, of such correlation. We estimate (11) via FGLS, postulating that the individual household variance depends on several observable characteristics (such as landholdings or household size) in the following way:

$$\tau_h^2 = \tau^2 \cdot \exp(\beta' z_h).$$

[20] We have conducted a White general test for heteroskedasticity, as well as one suggested by Glesjer based on the regression of the squared residuals on several household variables.

The regression equation (11) has been estimated numerous times in the literature on efficient risk sharing, for the special case in which $\alpha^h = \alpha^k = \alpha$ $\forall\ h, k$. Under the null hypothesis of full risk sharing in the village as a whole, equation (7) implies that $\alpha$ must be equal to zero, as changes in individual consumptions should comove at every period $t$ and not depend on any measure of household idiosyncratic shocks. A significantly positive estimated coefficient $\widehat{\alpha}$ implies that the full risk-sharing hypothesis can be rejected for the village as a whole.[21]

For the purposes of this paper, we are more interested in identifying specific households for which the implications of full risk-sharing models are rejected. We consider such households to be vulnerable to income fluctuations, and more generally to idiosyncratic risk. Therefore, we estimate a separate $\alpha^h$ parameter for each household $h$. A household is defined to be vulnerable if the estimated parameter $\widehat{\alpha}^h$ is statistically significantly positive. In addition, we take the point estimate $\widehat{\alpha}^h$ as our measure of vulnerability.

The baseline regression model (11) assumes that preference shocks are uncorrelated with the other covariates. As a robustness check, we also estimate a version of equation (7) where household specific medical expenditures $X_t^h$ in each period are used to proxy for the preference shock $\zeta_t^h$:

$$\Delta\widetilde{c}_t^h = \alpha^h \Delta\widetilde{y}_t^h + \phi_t \cdot MD_t + \delta X_t^h + \varepsilon_t^h \tag{12}$$

The regression equation (11) also assumes common risk aversion. While we do not have the degrees of freedom necessary to estimate a household specific risk aversion coefficient, it is possible to allow the coefficient of absolute risk aversion to vary across groups. Therefore, we also estimate the following version of the model:

$$\Delta\widetilde{c}_t^h = \alpha^h \Delta\widetilde{y}_t^h + \phi_{kt} \cdot MD_t \cdot HD_k + \varepsilon_t^h \tag{13}$$

where $HD_k$ is a Household Dummy that is equal to one if household $h$ is a member of group $k$, and zero otherwise, for $k = 1, ..., K,\ K < N$. In practice, we use female headship to distinguish two groups of households in each village ($K = 2$), thus estimating a separate $\phi_{kt} \equiv -\frac{1}{\sigma^k}\kappa_t$ parameter for female headed and male headed households. In principle, this enables

[21] Both villages in our dataset fail the full risk sharing test. For village $A$, $\widehat{\alpha} = 0.0366$ (with a p-value of 0.005) and for village $B$, $\widehat{\alpha} = 0.0299$ (with a p-value of 0.019).

us to estimate the ratio of the risk aversion coefficients for different types of households.

Finally, the counterpart to the baseline regression (11) for the CRRA case is the following:

$$\Delta \ln \widetilde{c}_t^h = \alpha^h \Delta \ln \widetilde{R}_t^h + \phi_t \cdot MD_t + \varepsilon_t^h, \tag{14}$$

where $\widetilde{R}_t^h$ represents per-adult-equivalent revenues for household $h$ at month $t$. We use revenues instead of income because the latter can sometimes take negative values, while the former cannot. At the same time, revenues are as good a proxy for idiosyncratic risk as income, and the theory only predicts that individual consumption should not be sensitive to any measure of individual shocks.

## 3.3 Estimation results

The baseline regression (11) and its CRRA counterpart (14) were estimated separately for each village. With CARA utility, we found 19 vulnerable households in village $A$ and 18 in village $B$, using a 10% statistical significance level.[22] With CRRA utility, we found 36 vulnerable households in both villages, at the 10% significance level. The distribution of the estimated $\widehat{\alpha}^h$ in each case is depicted in Figure 4. The mean of the vulnerability coefficients is 0.11 in village $A$ and 0.19 in village $B$ for the CARA case, 0.14 in $A$ and 0.20 in $B$ for the CRRA case.

The theoretical framework only offers a test of whether full risk sharing holds for a given household, but we need an alternative model to interpret the size of a significantly positive vulnerability coefficient. One possibility is to consider complete autarky, in which households consume out of their income every period, as the extreme alternative to the full risk-sharing model. Under this alternative, $\alpha^h$ would be expected to be close to unity. A household that finds itself in a situation of complete autarky would experience the maximum amount of vulnerability, since it would be completely unable to smooth its consumption in the face of idiosyncratic risk. As the household moves from full risk sharing to complete autarky, its $\alpha^h$ parameter will increase from zero to unity.[23] The higher $\widehat{\alpha}^h$ is, the more vulnerable the household is.

[22] These numbers fall to 14 and 10 respectively, using a 5% significance level.

[23] Only a couple of households, in either village and either utility specification, exhibit an estimated vulnerability parameter larger than one.

Roughly one quarter of the estimated parameters is negative. We consider households with negative $\widehat{\alpha}^h$ as not vulnerable at all, since contemporaneous income shocks do not seem to impose binding constraints on their consumption decisions. Instead (unobservable) preference shocks probably dictate their fluctuations in consumption.

# 4 Who are the poor and vulnerable?

In this section, we ask if there are any observable characteristics associated with poverty and vulnerability in the two villages.

Table 5 reports the results of OLS regressions of average monthly consumption for each household on a set of observable household characteristics. Poverty (as measured by low levels of consumption) is associated with smaller landholdings, female headed households, larger households, and households that have uneducated heads, in both villages. In village $B$, poverty is also associated with households that have more old people. These results are fairly intuitive.

The orders of magnitude for some of these associations are high. Column (5) of Table 5 shows that, everything else being equal, the predicted monthly consumption for male headed households exceeds the predicted monthly consumption for female headed households by 119 taka in village $A$ (nearly a third of the village average), and by 75 taka in $B$. A household head with some formal education increases his or her household consumption on average by 56 taka in village $A$ and 89 taka in village $B$ with respect to a household where the head has no education. The link between poverty and number of old people in village $B$ is intriguing: an additional old person in the household reduces average consumption by 54 taka.[24]

It is harder to find observable household characteristics that are readily associated with vulnerability. Table 6 presents the results of regressing vulnerability on household characteristics for both villages. The vulnerability coefficients come from the estimates of $\alpha^h$ based on equation (11), which assume a common coefficient of absolute risk aversion across households.

Female heads are more vulnerable in village $B$.[25] Table 6 indicates that, keeping other characteristics constant, female headed households have a pre-

[24]This result could be spurious, however, because of the arbitrariness of our age-sex weights.

[25]This result holds also for the CRRA vulnerability estimates.

dicted vulnerability coefficient that is 0.35 higher than male headed households in village $B$. To get an idea of the orders of magnitude, note that the mean of the vulnerability coefficients is 0.19 in village $B$. In addition, vulnerability is also significantly associated with households with older heads in village $A$.

In order to check the robustness of our vulnerability estimates, we consider a variety of alternative specifications in Table 7.[26] The first round of data collected in both villages is more susceptible to measurement error than subsequent rounds because the enumerators did not have a starting inventory of household grain and foodstuff to go by: this may increase the probability that consumption and income in that period are measured with error. In the second column of Table 7 we report our estimates excluding this first month of data.

Measurement error that is common to consumption and income would bias our vulnerability estimate in equation (11) upwards. There are important components of consumption (such as net meals received as wages and own produce consumed) that are also major components of income. One source of measurement error could well be the value of these meals (imputed by the enumerators to be approximately 7 taka with seasonal variations). Therefore, in the third and fourth columns of Table 7 we use consumption and income numbers that have higher and lower imputed values for net meals received as wages.

The fifth column of Table 7 reports our results with medical expenditures used as a proxy for household preference shocks (see equation (12)). Sickness shocks could reduce a household's desire to consume, for instance, and could be correlated with income changes. Finally, the sixth column uses vulnerability estimates obtained from regression (13), where the risk aversion parameter of female headed households is allowed to differ from that of male headed households.

The results of the baseline model are roughly confirmed. In particular, the finding that female headed households are more vulnerable than male headed ones in village $B$ holds across all different model specifications that attempt to address potential measurement error problems, preference shocks, and different risk aversion parameters for different types of households. As we mentioned in Section 2, the restrictions imposed by social customs on female heads may prevent them from engaging in economic activities that could help

[26] The first column simply reproduces the results in column (5) of Table 6, as a baseline.

them diversify their income sources and thus better face idiosyncratic risk.

Moreover, within the set of female headed households, divorcees are likely to be excluded from kinship, friendship, and other risk sharing networks, because of the social stigma attached to divorce. The fact that divorcees are relatively more abundant in village $B$ may explain why the association between vulnerability and female headship is statistically significant only in this village.

Table 7 also indicates that the age of the household head is positively associated with vulnerability in village $A$ for most specifications, but is negatively associated with vulnerability in village $B$. Therefore, older households are more vulnerable in $A$ but less vulnerable in $B$, after controlling for other characteristics such as landholdings, household size and household structure. One possible explanation for this difference is related to the fact that villagers in $B$ have more opportunities to diversify their income sources relative to $A$. In particular, a household with an older head is more likely to own more arable land in both villages. However, in village $B$, more land is associated with higher income from non agricultural sources, such as trade, businesses or rent. The reverse is true in village $A$.[27] Therefore, households with older heads have access to more diversified sources of income in $B$: this may allow them to have smoother income streams and to better insure themselves against risk.[28]

# 5 Does microcredit reach the poor and vulnerable?

In this Section, we first test if member households are poorer and more vulnerable than non-member households in each village using a first order stochastic dominance test based on Anderson [4] and described in the ap-

[27] The correlation coefficient between age of the household head and arable land is 0.27 in village $A$ and 0.18 in village $B$. The correlation coefficient between arable land and non agricultural income is $-0.07$ in $A$ and 0.17 in $B$.

[28] Given a consumption smoothing technology such that the cost of smoothing depends on the absolute size of the fluctuations to be eliminated, a household with a smoother income stream is likely to be able to smooth out a larger fraction of its income fluctuations (and thus appear to be less vulnerable) than a household that starts off with a more volatile income.

pendix.[29] Then we check if microcredit members are indeed in the lower quintiles of the poverty distribution and vulnerability. Finally, we test if our results remain the same if we control for other household characteristics that influence the decision to join a microcredit program.

## 5.1 Poverty

We compare the CDFs of average monthly consumption and income for microcredit members and non members in Figure 5. In both villages, and more so in village $B$, the distribution for non-members is shifted to the right. More formally, the non-parametric tests reported in Table 8 show that the distribution of consumption and income for non-members first order stochastically dominates the distribution for members in both villages. Therefore, microcredit members are significantly poorer than non-members in consumption and income terms in both villages (using a 10% significance level), and especially so in village $B$.

A probit regression of microcredit membership on average consumption in column 2 of Table 10 goes in the same direction as the stochastic dominance tests. Average consumption levels are negatively and significantly related to the decision to join in both villages: a 100 taka decrease in monthly consumption gives a household a 6% higher probability of receiving a loan on average. Controlling for other household characteristics, however, the association between microcredit membership and average consumption in village $B$ disappears (see columns 5 and 6 of Table 10).

Since a third of the sampled households had received loans by 1995, microcredit would have succeeded in (almost perfectly) targeting the poor if all the member households were at the bottom two quintiles of the distribution of average monthly consumption for the sample. But the data reveal that only 50% of the microcredit members in village $A$ and 57% of the microcredit members in village $B$ were in the bottom two quintiles. Similarly for average income: 42% of the members in village $A$ and 45% of the members in village $B$ were in the bottom two quintiles of the income distribution. So microcredit is far from perfectly targeting the poorest households.

[29] This is a non parametric test to see whether the distribution of, say, average monthly consumption for non-members first order dominates that for members. If it does, then we have a very strong indication that members are poorer than non-members, since first order stochastic dominance implies both second and third order dominance.

We can also evaluate the success of microcredit programs in reaching the poor using the poverty line. We mentioned in Section 2 that 68% of the sampled households in $A$ and 54% in $B$ are below the poverty line defined for the Rajshahi region. Table 11 shows that, among microcredit members, the percentage of households below the poverty line rises to 78% and 71% in village $A$ and $B$, respectively. Therefore, the probability that a microcredit member household is poor is substantially higher (especially in $B$) than the probability that a randomly picked household is below the poverty line.

In summary then, microcredit members are poorer than non-members in both villages, with a stronger and more significant effect for village $B$. Our results are subject to the following caveat. Since a third of the microcredit members in village $B$ joined before the end of the twelve rounds of data collection in 1992, there is the possibility that the loans received from the Grameen Bank may make members richer, thus biasing our results. Under the assumption that membership must have a non-negative impact on household consumption, we may be underestimating microcredit's effectiveness at reaching the poor in village $B$. Such a bias will only strengthen our result here, since we already find that microcredit members in village $B$ are poorer than non-members. For village $A$, the bias is likely to be smaller, since only few households had joined microcredit before the end of the $1991-92$ survey, and again it would go in the direction of strengthening our findings.

## 5.2 Vulnerability

We now turn to the relationship between vulnerability and microcredit membership. Table 9 contains the first order stochastic dominance test results. The CDFs of vulnerability for members and non-members are plotted in Figure 6. There is evidence (at the 10% significance level) that non-members are more vulnerable than members in village $A$, whereas in $B$ it is microcredit members who appear to be more vulnerable. This result holds regardless of the type of utility function employed to estimate vulnerability. Moreover, when we use the different specifications of Table 7 to take into account measurement error, preference shocks, and household heterogeneity with respect to risk aversion, the findings are confirmed and in some cases become significant at the 5% level. Therefore, it seems that microcredit does reach more vulnerable households in village $B$, whereas it is less successful at doing so in $A$.

Table 11 yields the same conclusion. In this table, a vulnerable household is defined as having an estimated $\widehat{\alpha}^h$ parameter that is statistically significantly positive. Here the percentage of vulnerable households among microcredit members can be compared to the fraction of vulnerable households in our sample. The probability that a randomly picked household in village $A$ is vulnerable is 19%, while the percentage of microcredit members who are vulnerable is just 15%. For village $B$, in contrast, the probability that a randomly picked household is vulnerable is 14%, while the percentage of microcredit members who are vulnerable is 19%.[30]

We can now go back to the timing problem that we mentioned in Section 2. Since a third of the microcredit members in village $B$ joined before the end of the twelve rounds of data collection in 1992, there is the concern that the loans received from the Grameen may alter members' ability to intertemporally smooth consumption, thus making them appear less vulnerable than they actually were before joining. We assume here that membership can only reduce a household's vulnerability or leave it unaltered. Consequently, since some members may appear to us less vulnerable than they actually were before joining, we may underestimate microcredit's effectiveness at reaching the vulnerable in village $B$. Such a bias would only strengthen our result here, since we already find that microcredit members in village $B$ are more vulnerable than non-members. For village $A$, the bias is likely to be very small, so it is very unlikely to overturn the result of our stochastic dominance test.

We know that microcredit members represent roughly one third of our sample of households in both villages from Table 3. If microcredit programs were able to perfectly target the most vulnerable households, their members should come from the top third of the distribution of vulnerability. For simplicity, we divide the distribution of vulnerability estimates into quintiles, and ask what percentage of microcredit members come from the top two quintiles of that distribution. Under perfect targeting, all members should be found within these two top quintiles. It turns out that only 37% of microcredit members are in the top two quintiles of the vulnerability distribution in village $A$, whereas 53% of all members are in the two highest quintiles of the distribution in $B$.[31] Again, given the possibility of bias in village $B$, these numbers indicate that microcredit does relatively well in village $B$, whereas for village $A$ the degree of mistargeting of the most vulnerable is substantial.

[30] These proportions have been adjusted to correct for the oversampling of female headed households in our dataset.

[31] This is for CARA utility. With CRRA, the corresponding statistics are 32% for village A, and 45% for B. Thus the pattern is preserved.

Finally, the probit regression of microcredit membership on vulnerability (with CARA utility) is reported in Table 10. The results are inconclusive for village $A$. However, there is some evidence that microcredit reaches the more vulnerable in $B$. In column (1), the coefficient associated with vulnerability in $B$ is positive and only barely insignificant at the 10% level. Quantitatively, the point estimate suggests that increasing the vulnerability coefficient from zero to one raises the probability of being a microcredit member by 12%. This estimate remains quite stable even as one adds controls for other household characteristics, although its statistical significance drops.

# 6 Targeting strategies

In this section, we use our results to evaluate current microcredit strategies, such as targeting the landless and restricting loans to women, in terms of the objective of reaching the poorest and most vulnerable.

Microcredit does relatively well at targeting crucial household categories in both villages. Female headship is significantly associated with poverty in both villages, and with vulnerability in village $B$. Table 10 shows that female headed households in $B$ have a 16% higher chance of joining a microcredit program than male headed ones. Further, from Table 12 we see that in village $B$, 48% of the female headed households are microcredit members, while only 27% of the male headed households are members. Households with younger heads have a higher probability of joining microcredit programs in both villages (from Table 10): we know from Tables 6 and 7 that younger households are more vulnerable in $B$, but less vulnerable in $A$. A household with an uneducated head is not significantly more likely to join in village $A$ (from Table 10), but this household category is significantly poorer in both villages. In village $B$, households with uneducated heads have a 20% higher chance of joining, and there microcredit is reaching the right group.

Let us consider now the one targeting criterion that microcredit programs actually use: landlessness. Households with less than half an acre of cultivated land are considered landless and eligible by Grameen, BRAC and ASA. But Table 3 shows that only 14 of the 38 members in village $A$ and 17 of the 38 members in village $B$ were landless according to the 1992 data. This means that over 60% of the sampled households that joined in both villages were ineligible by the landholding criterion.[32] Table 12 shows that in village

[32] These may be overestimates. Households may have either split or sold land after

$B$ microcredit reached a higher proportion of the landless than of the landed, while in village $A$, microcredit reached a higher proportion of the landed than the landless.

How good a criterion is landlessness for targeting the poor and vulnerable anyway? A scatterplot of arable landholdings and average consumption levels in Figure 7 shows that the relationship between poverty and landlessness is weak. Controlling for other household characteristics, more arable land is associated with higher consumption in both villages (from Table 5), but the magnitude of this relationship is very small: one additional acre of arable land is associated with an increase in predicted consumption of 3 taka in $A$ and 6 taka in $B$.[33] Furthermore, Tables 6 and 7 show that a household's arable landholdings are not significantly associated with vulnerability in either village.[34] Targeting the landless, therefore, is not the best strategy for an anti-poverty credit program in these two Rajshahi villages. So the leakage of credit to the landed is not a cause for alarm.

The above analysis does suggest an alternative target group: female headed households. These households have lower average consumptions and incomes than male headed households in both villages (from Table 4). Even controlling for other characteristics, this category is poorer in both villages, and more vulnerable in village $B$ (from Tables $5, 6$ and 7). A microcredit program that targets female headed households would have more success at reaching the poor and vulnerable than one that targets the landless.

Field evidence also indicates that female headship is the appropriate target group: older female headed households are the only ones for whom begging is socially sanctioned in these villages. Younger female headed households, of whom most are divorcees, are excluded from begging and thus cannot use this as a smoothing device. As we have mentioned in Section 2, divorcees are relatively more abundant in village $B$: this could explain why female headed households are significantly vulnerable in $B$ but not in $A$. In addition, Amin [3] reports that the negative consequences of female headship are perpetuated through the generations: 27% of female headed households

1992 prior to joining microcredit programs. Interestingly though, Morduch [13] finds that 20$-$30% of borrowers are ineligible using a sample of nearly 1800 households in Bangladesh.

[33] The mean landholdings in the two villages are roughly 9 acres in $A$ and 7.7 acres in $B$. The distribution of land is very skewed: the median in village $A$ is 1.2 acres, whereas in $B$ it is 1.5 acres.

[34] The same result holds if we use a landlessness dummy variable, that classifies households into landless if they have less than $\frac{1}{2}$ an acre of arable land.

in the sample report a separated or divorced daughter, compared with less than 5% in male headed households.

Table 13, which is based on a nationally representative survey, shows that although all three programs restrict loans to women, Grameen and ASA both appear to favor married women over those who are widowed or divorced. BRAC reaches a higher proportion of divorcees and only a slightly lower proportion of widows than the average.

Finally, it is worth noting that microcredit programs are significantly better at reaching the poor than (untargeted) government bank loans. Three households in village $A$ with average consumption of 560 taka and average income of 1150 taka received government loans. 11 households in village $B$ with an average consumption of 591 taka and an average income of 943 taka received loans. These are substantially richer households than those who received microcredit (see Table 4).

# 7 Conclusions

This paper uses panel data from two Bangladeshi villages to test if microcredit reaches the poor and vulnerable. This analysis is possible due to the convenient timing in our data set. Households were extensively surveyed in $1991-92$, when microcredit programs had only a small presence in the study villages. Households were subsequently resurveyed in 1995 by which time microcredit programs had firmly established themselves.

Bangladesh is an appropriate place for such a study, because it is the hub of microcredit innovation. The three programs in our study, Grameen Bank, BRAC and ASA, are the largest microcredit providers in Bangladesh, and among the largest in the world. Estimates suggest that one quarter of Bangladesh's population of 120 million has a family member with access to small subsidized loans (Financial Times, [7]).

Our results show that microcredit is successful at reaching the poor. The probability that a microcredit member is below the poverty line is substantially higher than that of a randomly chosen household. In addition, microcredit members are significantly poorer than non members in both villages. Critics of subsidized credit schemes typically argue that the subsidies are diverted to the rich. We argue that credit should not be dismissed as a means to fund the poor, at least not on these grounds.

Though microcredit programs in Bangladesh target loans to the landless, this eligibility criterion is not enforced in practice. Our results therefore show that there must be some other selection device used to reach the poor. By offering small loans, by requiring weekly attendance and by providing only moderate subsidies, microcredit programs may be inducing the rich not to participate. We show that if microcredit programs did want to explicitly target a particular group, targeting loans to female headed households would be more effective in reaching the poor than targeting the landless.

One of the contributions of this paper is to link the tests of risk sharing and efficiency in village economies with anti-poverty and credit interventions. The existence of vulnerable households in these two villages is a sign of market and institutional failures. Therefore, an argument can be made for anti-poverty programs to include these households on both equity and efficiency grounds. The same forces that make some households vulnerable may also make them greater risks for small loan providers, however. For that reason, it is remarkable that at least in one of the villages in our study microcredit members are more vulnerable than non-members.

The results here also raise the intriguing possibility that there may be limits to microcredit's reach in more remote agricultural areas. Since microcredit programs require weekly repayments and are focused on non-farm credit, they may do better at reaching the poor and vulnerable in villages where the opportunity for diversification exists (like village $B$).[35] This result is consistent with Morduch [12], who notes that the microcredit movement worldwide has yet to make inroads in areas focused on agricultural cultivation.

# 8 Appendix: first order stochastic dominance tests

The tool that we adopt to address the question of whether microcredit reaches the poor and vulnerable is a test of first order stochastic dominance, developed by Anderson [4]. In fact, our question translates into checking whether microcredit members were poorer or more vulnerable (in terms of the 1991-92 transactions data) than non-members. Instead of looking at specific moments of the distribution of the variable of interest for members and non-members,

[35] Since we have only two villages in our study, the differences in microcredit reach across the two may also just be a function of the diligence of the bank officers assigned to each.

however, we prefer to take a more general approach and use the concept of stochastic dominance. In particular, we ask whether the distribution of, say, average monthly consumption of non-members first order dominates that of members. If we can answer in the positive, then we have a very strong indication that members are poorer than non-members.[36] Intuitively, it means that the consumption distribution for non-members is unambiguously shifted to the right compared to that of members. Formally, let $C$ be the range of consumptions from two consumption distributions $N$ (for non-members) and $M$ (for members) with cumulative distribution functions $F_N(c)$ and $F_M(c)$, respectively. First order stochastic dominance of distribution $N$ over $M$ is equivalent to the condition:

$$F_N(c) \leq F_M(c),\ F_N(c_i) \neq F_M(c_i) \text{ for some } i,\ \ \forall c \in C. \tag{15}$$

The test of first order stochastic dominance is quite straightforward. The idea is to partition the combined sample for $N$ and $M$ into $k$ equal intervals and compute the empirical frequencies of the $N$ and $M$ samples in each interval: for example, $p_i^N = \frac{x_i^N}{n^N}$, $i = 1, ..., k$, where $x_i^N$ is the number of observations in the $N$ sample that fall in interval $i$, and $n^N$ is the total number of observations in the $N$ sample. Let $I_f$ be a $k \times k$ lower-triangular matrix of ones. Since the cumulative distribution function at a point $j$ can be computed as $F(c_j) = \sum_{i=1}^{j} p_i$, a test of condition (15) translates into the following hypothesis test:

$$H_0 : I_f(p^N - p^M) = 0 \ \text{ against } \ H_1 : I_f(p^N - p^M) \leq 0. \tag{16}$$

In particular, first order dominance of distribution $N$ over $M$ requires that no element of the vector $I_f(p^N - p^M)$ be significantly greater than zero, while at least one element is significantly negative. The test is symmetric, so first order dominance of distribution $M$ over $N$ requires that no element of the vector $I_f(p^N - p^M)$ be significantly negative, while at least one element is significantly positive. Finally, the test statistic $I_f(p^N - p^M)$ is asymptotically distributed as a $N(0, I_f V I_f')$ under the null hypothesis, where $V$ can be estimated using the empirical frequencies $p$ of the combined sample.[37]

[36] In fact, first order stochastic dominance implies both second and third order dominance.

[37] See Anderson [4] for the details.

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TABLE 1

PRIMARY OCCUPATION OF HEAD OF HOUSEHOLD

| | Village A* | Village B* |
|---|---|---|
| Agriculture | 48.7 | 27.6 |
| Daily Labor | 29.8 | 21.6 |
| Fishing | 2.0 | 0.0 |
| Trading | 6.3 | 11.8 |
| Government & NGO Service | 1.8 | 11.3 |
| Teaching | 0.0 | 3.3 |
| Local Transport | 1.5 | 7.9 |
| Others** | 9.8 | 15.8 |

*Percentage of households.
**Others include Poultry/Cattle Rearing, Maid Servants, Beggars, Handicraft workers, Students, Servants, Medical Doctors and assistants, Pensioners, Skilled Workers.

## TABLE 2

### SUMMARY STATISTICS*

| | VILLAGE A (112 Households) | | | VILLAGE B (117 Households) | | |
|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | CV | Mean | Std. Dev. | CV |
| Food Consumption | 324.00 | 171.05 | 0.53 | 351.73 | 227.61 | 0.65 |
| All Consumption | 388.38 | 210.35 | 0.54 | 466.93 | 308.29 | 0.66 |
| All Income | 429.69 | 347.49 | 0.81 | 537.62 | 564.04 | 1.05 |
| All Revenue | 537.23 | 467.85 | 0.87 | 681.84 | 713.47 | 1.05 |
| Medical Expenditures | 36.06 | 50.37 | 1.40 | 57.56 | 77.20 | 1.34 |
| Household Size | 4.64 | 2.43 | 0.52 | 4.60 | 2.02 | 0.44 |
| Age of HH Head | 41.77 | 14.34 | 0.34 | 43.66 | 13.97 | 0.32 |
| Number of children | 1.66 | 1.30 | 0.78 | 1.57 | 1.20 | 0.77 |
| Number of Old People | 0.19 | 0.46 | 2.35 | 0.21 | 0.45 | 2.11 |
| Agricultural Land | 904.99 | 2750.02 | 3.04 | 766.45 | 1980.07 | 2.58 |

*All statistics are weighed to correctly reflect the proportion of female-headed households in the population.
*The first five variables are measured in units of 1992 taka per adult equivalent per month. Agricultural land is measured in decimals (100 decimals = 1 acre).
*Exchange Rate in 1992 was US $1=38 taka.

TABLE 3

HOUSEHOLD CATEGORIES AND MICROCREDIT MEMBERSHIP

| | Village A | Village B |
|---|---|---|
| Total Number of Sampled Households | 112 | 117 |
| Landless (arable land <= 0.5 acres) | 42 | 47 |
| Landed | 70 | 70 |
| Female-headed | 24 | 31 |
| Male-headed | 88 | 86 |
| Uneducated Household Head | 71 | 71 |
| Educated Household Head | 41 | 46 |
| Members of Microcredit NGO | 38 * | 38 ** |
| Non-members | 74 | 79 |
| Members of ASA | 12 | 3 |
| Members of BRAC | 16 | 19 |
| Members of Grameen | 10 | 17 |

*14 microcredit members were landless in 1992 in Village A.
**17 microcredit members were landless in 1992 in Village B.
In Village B, one HH is a member of both BRAC and Grameen.

# TABLE 4

## CONSUMPTION AND INCOME BY HOUSEHOLD CATEGORY*

| CATEGORY | VILLAGE A Mean | VILLAGE A Std. Dev. | VILLAGE A CV | VILLAGE B Mean | VILLAGE B Std. Dev. | VILLAGE B CV |
|---|---|---|---|---|---|---|
| Landless (arable land <= 0.5 acres) | | | | | | |
| Consumption | 346.11 | 236.06 | 0.68 | 365.87 | 251.39 | 0.69 |
| Income | 309.86 | 240.86 | 0.78 | 390.06 | 446.31 | 1.14 |
| Landed | | | | | | |
| Consumption | 413.73 | 190.61 | 0.46 | 534.79 | 325.60 | 0.61 |
| Income | 501.60 | 381.83 | 0.76 | 636.69 | 614.22 | 0.96 |
| Female-headed | | | | | | |
| Consumption | 331.27 | 152.93 | 0.46 | 369.34 | 178.55 | 0.48 |
| Income | 227.93 | 179.81 | 0.79 | 271.21 | 202.15 | 0.75 |
| Male-headed | | | | | | |
| Consumption | 392.27 | 136.47 | 0.35 | 475.73 | 207.77 | 0.44 |
| Income | 443.45 | 274.98 | 0.62 | 561.62 | 460.97 | 0.82 |
| Uneducated HH Head | | | | | | |
| Consumption | 336.91 | 197.81 | 0.59 | 345.04 | 226.54 | 0.66 |
| Income | 347.18 | 258.02 | 0.74 | 331.88 | 287.67 | 0.87 |
| Educated HH Head | | | | | | |
| Consumption | 477.49 | 203.64 | 0.43 | 655.07 | 324.87 | 0.50 |
| Income | 572.58 | 430.77 | 0.75 | 855.17 | 722.16 | 0.84 |
| Members of Microcredit NGO | | | | | | |
| Consumption | 377.15 | 172.34 | 0.46 | 335.93 | 229.72 | 0.68 |
| Income | 387.89 | 214.91 | 0.55 | 401.31 | 416.12 | 1.04 |
| Non-members | | | | | | |
| Consumption | 394.14 | 228.31 | 0.58 | 529.95 | 322.38 | 0.61 |
| Income | 451.16 | 398.52 | 0.88 | 603.18 | 614.48 | 1.02 |

*All statistics are weighed to correctly reflect the proportion of female-headed households in the population.
*All variables are measured in units of 1992 taka per adult equivalent per month.
*Exchange Rate in 1992 was US $1=38 taka.

# TABLE 5

## LINEAR REGRESSION OF AVERAGE CONSUMPTION ON HOUSEHOLD CHARACTERISTICS

| | VILLAGE A | | | | | VILLAGE B | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1)* | (2)* | (3)* | (4)* | (5)* | (1)* | (2)* | (3)* | (4)* | (5)* |
| Agric. Land | 0.0068 | | 0.0056 | 0.0242 | 0.0292 | 0.0557 | | 0.0535 | 0.0578 | 0.06 |
| | (0.21) | | (0.30) | (0.00) | (0.00) | (0.00) | | (0.00) | (0.00) | (0.00) |
| Female headed | | -102.25 | -74.2 | -113.39 | -118.61 | | -64.18 | -42.61 | -82.64 | -74.75 |
| | | (0.01) | (0.03) | (0.01) | (0.00) | | (0.06) | (0.18) | (0.02) | (0.03) |
| Age of HH Head | | | | 0.3723 | | | | | 1.38 | |
| | | | | (0.74) | | | | | (0.22) | |
| Household Size | | | | -27.1 | -40.98 | | | | -29.91 | -28.62 |
| | | | | (0.05) | (0.00) | | | | (0.01) | (0.00) |
| HH Structure | | | | -0.6318 | | | | | 4.96 | |
| | | | | (0.96) | | | | | (0.61) | |
| Uneducated Head | | | | -44.02 | -55.76 | | | | -93.54 | -88.6 |
| | | | | (0.15) | (0.06) | | | | (0.00) | (0.00) |
| No. of Children | | | | -19.08 | | | | | -10.28 | |
| | | | | (0.28) | | | | | (0.50) | |
| No. of Old People | | | | -47.86 | -33.05 | | | | -78.92 | -54.21 |
| | | | | (0.19) | (0.28) | | | | (0.03) | (0.08) |
| Adjusted R-squared | 0.1998 | 0.0311 | 0.2124 | 0.3438 | 0.3472 | 0.1998 | 0.0311 | 0.2124 | 0.3438 | 0.3472 |

*p-values are reported in parentheses.

## TABLE 6

LINEAR REGRESSION OF VULNERABILITY ON HOUSEHOLD CHARACTERISTICS

| | Village A | | | | | Village B | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1)* | (2)* | (3)* | (4)* | (5)* | (1)* | (2)* | (3)* | (4)* | (5)* |
| Agric. Land | -0.0 | | -0.0 | -0.0 | -0.0 | -0.0 | | -0.0 | -0.0 | -0.0 |
| | (0.49) | | (0.72) | (0.87) | (0.83) | (0.54) | | (0.71) | (0.71) | (0.65) |
| Female headed | | 0.0021 | -0.0034 | -0.2143 | -0.204 | | 0.347 | 0.3413 | 0.345 | 0.347 |
| | | (0.98) | (0.97) | (0.13) | (0.12) | | (0.00) | (0.00) | (0.00) | (0.00) |
| Age of HH Head | | | | 0.0063 | 0.0074 | | | | -0.0003 | -0.0008 |
| | | | | (0.08) | (0.02) | | | | (0.93) | (0.79) |
| Household Size | | | | -0.0074 | -0.0078 | | | | 0.0162 | 0.0151 |
| | | | | (0.87) | (0.78) | | | | (0.64) | (0.56) |
| HH Structure | | | | -0.056 | -0.0549 | | | | -0.0154 | -0.016 |
| | | | | (0.14) | (0.11) | | | | (0.62) | (0.59) |
| Uneducated Head | | | | 0.0739 | | | | | 0.01 | |
| | | | | (0.45) | | | | | (0.92) | |
| No. of Children | | | | 0.0072 | | | | | -0.0023 | |
| | | | | (0.90) | | | | | (0.96) | |
| No. of Old People | | | | 0.071 | | | | | -0.0348 | |
| | | | | (0.54) | | | | | (0.75) | |
| Adjusted R-squared | -0.0053 | 0.0533 | 0.0458 | 0.038 | 0.0596 | -0.0053 | 0.0533 | 0.0458 | 0.038 | 0.0596 |

*p-values are reported in parentheses.

# TABLE 7

SENSITIVITY ANALYSIS OF VULNERABILITY REGRESSION
DEPENDENT VARIABLE: VULNERABILITY

| | Baseline* | Truncated* | High* | Low* | Med. Exp.* | Female* |
|---|---|---|---|---|---|---|
| VILLAGE A | | | | | | |
| Agric. Land | -0.0 | 0.0 | -0.0 | -0.0 | -0.0 | -0.0 |
| | (0.83) | (0.96) | (0.76) | (0.78) | (0.77) | (0.78) |
| Female headed | -0.204 | -0.3473 | -0.2101 | -0.2331 | -0.1934 | -0.2807 |
| | (0.12) | (0.05) | (0.20) | (0.17) | (0.13) | (0.09) |
| Age of HH Head | 0.0074 | 0.013 | 0.0031 | 0.0027 | 0.0077 | 0.0083 |
| | (0.02) | (0.00) | (0.41) | (0.47) | (0.01) | (0.03) |
| Household Size | -0.0078 | -0.0479 | 0.004 | 0.007 | -0.0079 | -0.0048 |
| | (0.78) | (0.22) | (0.91) | (0.85) | (0.78) | (0.89) |
| HH Structure | -0.0549 | -0.0374 | -0.0278 | -0.0284 | -0.0488 | -0.0575 |
| | (0.11) | (0.42) | (0.52) | (0.52) | (0.14) | (0.18) |
| VILLAGE B | | | | | | |
| Agric. Land | -0.0 | -0.0 | -0.0 | -0.0 | -0.0 | -0.0 |
| | (0.65) | (0.63) | (0.63) | (0.62) | (0.52) | (0.62) |
| Female headed | 0.347 | 0.3055 | 0.3671 | 0.3243 | 0.3352 | 0.3919 |
| | (0.00) | (0.04) | (0.01) | (0.02) | (0.00) | (0.00) |
| Age of HH Head | -0.0008 | -0.0082 | -0.0087 | -0.0088 | -0.0004 | -0.0104 |
| | (0.79) | (0.04) | (0.02) | (0.02) | (0.88) | (0.00) |
| Household Size | 0.0151 | 0.0401 | 0.0428 | 0.0476 | 0.0209 | 0.0512 |
| | (0.56) | (0.25) | (0.19) | (0.15) | (0.41) | (0.11) |
| HH Structure | -0.016 | 0.0326 | 0.0292 | 0.0234 | -0.0127 | 0.0305 |
| | (0.59) | (0.42) | (0.44) | (0.54) | (0.67) | (0.41) |
| Adjusted R-squared | 0.0596 | 0.044 | 0.0173 | 0.0103 | 0.0597 | 0.0485 |

*p-values are reported in parentheses.

# TABLE 8

## POVERTY AND MICROCREDIT MEMBERSHIP
## TEST OF STOCHASTIC DOMINANCE

| CONSUMPTION COMPARISON | | | | | | INCOME COMPARISON | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Village A | | | Village B | | | Village A | | | Village B | | |
| Members minus Non-members | (t-statistics) | | Members minus Non-members | (t-statistics) | | Members minus Non-members | (t-statistics) | | Members minus Non-members | (t-statistics) | |
| -0.0142 | -0.3841 | | 0.0809 | 1.5387 | * | -0.058 | -0.736 | | 0.155 | 1.691 | * |
| 0.0220 | 0.2944 | | 0.1795 | 2.0403 | ** | 0.075 | 0.807 | | 0.104 | 1.117 | |
| 0.0797 | 0.7983 | | 0.3055 | 3.0947 | *** | 0.082 | 1.508 | * | 0.044 | 0.539 | |
| 0.1408 | 1.5347 | * | 0.1955 | 2.1300 | ** | 0.014 | 0.720 | | 0.087 | 1.396 | * |
| 0.0839 | 1.1450 | | 0.1849 | 2.1447 | ** | 0.014 | 0.720 | | 0.075 | 1.425 | * |
| 0.0156 | 0.2750 | | 0.0983 | 1.4125 | * | 0.014 | 0.720 | | 0.075 | 1.425 | * |
| 0.0405 | 1.2581 | | 0.0750 | 1.4247 | * | 0.014 | 0.720 | | 0.050 | 1.060 | |
| 0.0270 | 1.0226 | | 0.0886 | 1.8924 | ** | 0.014 | 0.720 | | 0.038 | 1.217 | |
| 0.0135 | 0.7198 | | 0.0380 | 1.2170 | | 0.014 | 0.720 | | 0.013 | 0.697 | |

The columns report the differences between the CDF of Members and Non-members, at several points. Under the null hypothesis that the two samples come from the same distribution, each term is distributed as a Student's t with (here) 9 degrees of freedom.The t-statistics are in parentheses. The distribution for Members first order dominates that for Non-members if no term is significantly greater than zero while at least one is significantly negative. Likewise, dominance of Non-members over Members requires than no term be significantly negative while at least one is significantly positive.

* Statistically significant at 90% level.

**Statistically significant at 95% level.

***Statistically significant at 99% level.

# TABLE 9

## VULNERABILITY AND MICROCREDIT MEMBERSHIP
## TEST OF STOCHASTIC DOMINANCE

| CARA UTILITY FUNCTION (SIGMA =1) | | | | | | CRRA UTILITY FUNCTION (GAMMA =1) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Village A | | | Village B | | | Village A | | | Village B | | |
| Members minus Non-members | (t-statistics) | | Members minus Non-members | (t-statistics) | | Members minus Non-members | (t-statistics) | | Members minus Non-members | (t-statistics) | |
| 0.0270 | 1.4111 | * | -0.0256 | -0.9957 | | -0.0142 | -0.3841 | | -0.0127 | -0.6965 | |
| 0.0404 | 1.2277 | | -0.0250 | -0.6214 | | 0.0910 | 1.7712 | * | -0.0127 | -0.6965 | |
| 0.0267 | 0.7056 | | -0.0209 | -0.2652 | | 0.0071 | 0.0844 | | -0.038 | -1.217 | |
| 0.0511 | 0.5959 | | -0.0965 | -1.2233 | | -0.0242 | -0.2463 | | -0.031 | -0.3886 | |
| 0.1385 | 1.7154 | * | -0.0405 | -0.9241 | | 0.1152 | 1.2194 | | -0.1552 | -1.6909 | * |
| 0.0007 | 0.0162 | | -0.0270 | -0.7477 | | 0.1387 | 1.6689 | * | -0.1083 | -1.7449 | * |
| 0.0411 | 1.2503 | | -0.0398 | -1.2679 | | 0.0697 | 1.0560 | | -0.0137 | -0.5337 | |
| 0.0274 | 1.0161 | | -0.0263 | -1.4389 | * | 0.0284 | 0.5535 | | -0.0137 | -0.5337 | |
| 0.0137 | 0.7152 | | -0.0263 | -1.4389 | * | 0.0142 | 0.3841 | | -0.0263 | -1.4481 | * |

The columns report the differences between the CDF of Members and Non-members, at several points. Under the null hypothesis that the two samples come from the same distribution, each term is distributed as a Student's t with (here) 9 degrees of freedom.The t-statistics are in parentheses. The distribution for Members first order dominates that for Non-members if no term is significantly greater than zero while at least one is significantly negative. Likewise, dominance of Non-members over Members requires than no term be significantly negative while at least one is significantly positive.

* Statistically significant at 90% level.

**Statistically significant at 95% level.

***Statistically significant at 99% level.

# TABLE 10

PROBIT REGRESSION OF MICROCREDIT MEMBERSHIP ON VULNERABILITY AND HOUSEHOLD CHARACTERISTICS

| | VILLAGE A | | | | | | VILLAGE B | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1)* | (2)* | (3)* | (4) | (5)* | (6)* | (1)* | (2)* | (3)* | (4)* | (5)* | (6)* |
| Vulnerability | -0.0742 | | | | -0.0392 | -0.0159 | 0.1241 | | | | 0.0815 | 0.0928 |
| | (0.55) | | | | (0.79) | (0.91) | (0.13) | | | | (0.36) | (0.30) |
| Average Consumption | | -0.0006 | | | -0.0008 | -0.0008 | | -0.0006 | | | -0.0003 | -0.0003 |
| | | (0.01) | | | (0.03) | (0.04) | | (0.00) | | | (0.22) | (0.20) |
| Landless | | | 0.012 | | -0.0679 | -0.0802 | | | 0.04 | | -0.0852 | -0.0869 |
| | | | (0.88) | | (0.53) | (0.45) | | | (0.61) | | (0.42) | (0.39) |
| Female headed | | | | -0.0692 | -0.1137 | | | | | 0.1646 | 0.087 | |
| | | | | (0.51) | (0.43) | | | | | (0.07) | (0.51) | |
| Age of HH Head | | | | | -0.0106 | -0.012 | | | | | -0.0101 | -0.008 |
| | | | | | (0.01) | (0.00) | | | | | (0.03) | (0.05) |
| Household Size | | | | | 0.0613 | 0.0575 | | | | | -0.0374 | -0.0458 |
| | | | | | (0.09) | (0.10) | | | | | (0.40) | (0.30) |
| Household Structure | | | | | -0.004 | 0.0066 | | | | | -0.0534 | -0.0523 |
| | | | | | (0.92) | (0.86) | | | | | (0.15) | (0.15) |
| Uneducated Head | | | | | 0.0597 | 0.0417 | | | | | 0.1755 | 0.1975 |
| | | | | | (0.56) | (0.68) | | | | | (0.09) | (0.05) |
| No. of Children | | | | | -0.1318 | -0.1209 | | | | | 0.0782 | 0.0797 |
| | | | | | (0.02) | (0.02) | | | | | (0.17) | (0.17) |
| No. of Old People | | | | | -0.0521 | | | | | | 0.0757 | |
| | | | | | (0.67) | | | | | | (0.57) | |
| Pseudo R-squared | 0.0101 | 0.0375 | 0.0009 | 0.0138 | 0.1494 | 0.1442 | 0.0101 | 0.0375 | 0.0009 | 0.0138 | 0.1494 | 0.1442 |

*The marginal effects dF/dx, evaluated at the sample mean, are reported here. P-values are reported in parentheses.

# TABLE 11

TARGETING STRATEGIES: PERCENTAGE OF POOR AND VULNERABLE HOUSEHOLDS AMONG LANDLESS, FEMALE HEADED AND MICROCREDIT MEMBERS*

| | Village A | | | | Village B | | | |
|---|---|---|---|---|---|---|---|---|
| | Non Poor | Poor | Non Vuln.** | Vuln.** | Non Poor | Poor | Non Vuln.** | Vuln.** |
| Total | 32 | 68 | 81 | 19 | 46 | 54 | 86 | 14 |
| Landless | 33 | 67 | 76 | 24 | 33 | 67 | 89 | 11 |
| Female-headed | 29 | 71 | 92 | 8 | 29 | 71 | 77 | 23 |
| MC Member | 22 | 78 | 85 | 15 | 29 | 71 | 81 | 19 |

* Each cell reports the percentage of the row category that falls into the column category.
All percentages are weighted to accurately reflect the oversampling of female headed households.
**Vulnerability is estimated using CARA utility.

## TABLE 12

MICROCREDIT MEMBERSHIP BY HOUSEHOLD CATEGORIES*

| | Village A | Village B |
|---|---|---|
| Landless | 33 | 36 |
| Landed | 37 | 24 |
| | | |
| Female Headed | 25 | 48 |
| Male Headed | 36 | 27 |

*Each cell reports the percentage of microcredit members among the row household category. All percentages are weighted to accurately reflect the oversampling of female headed households.

# TABLE 13

MARITAL STATUS DISTRIBUTION OF EVER MARRIED WOMEN BY MEMBERSHIP IN NGOS, 1996-97*

| Marital Status | All ever married women | BRAC | ASA | Grameen |
|---|---|---|---|---|
| Married | 92.8 | 93.7 | 96.9 | 95.4 |
| Widowed | 4.4 | 3.1 | 1.6 | 2.8 |
| Divorced | 2.8 | 3.1 | 1.6 | 1.8 |

*Source: Bangladesh Demographic and Health Surveys, 1996-97.

Figure 1a. Comovement of household income (deviations from village average): Village A

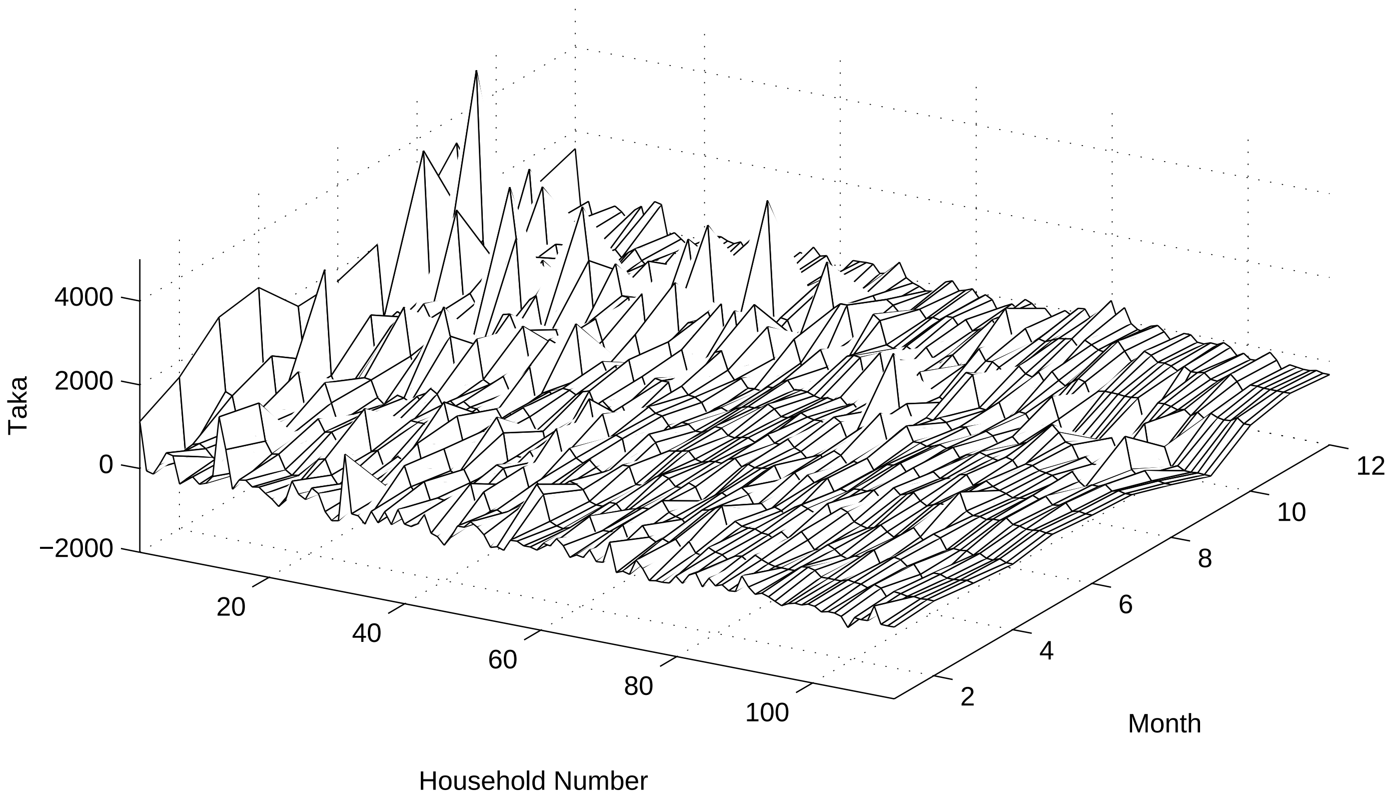



Figure 1b. Comovement of household income (deviations from village average): Village B

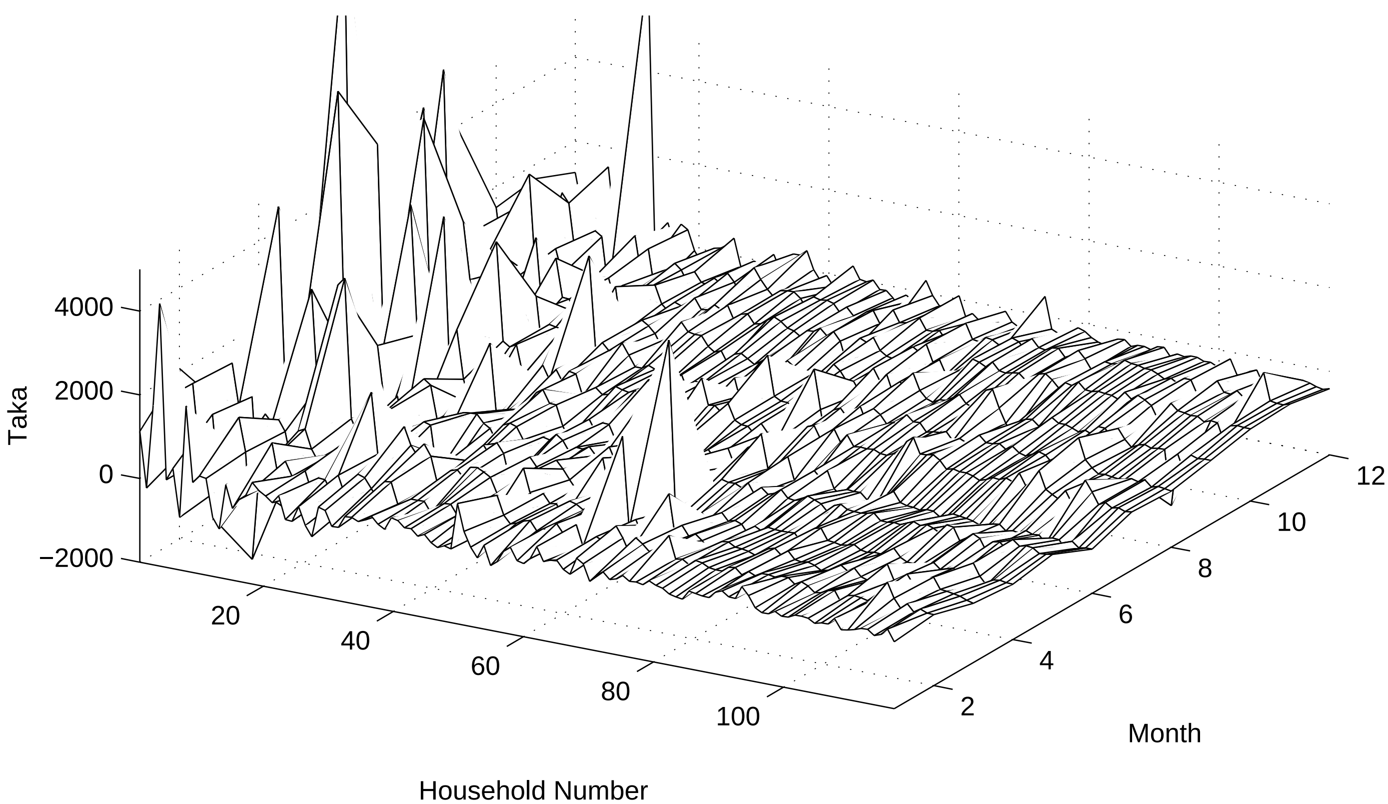


Figure 2a. Comovement of household revenue (deviations from village average): Village A

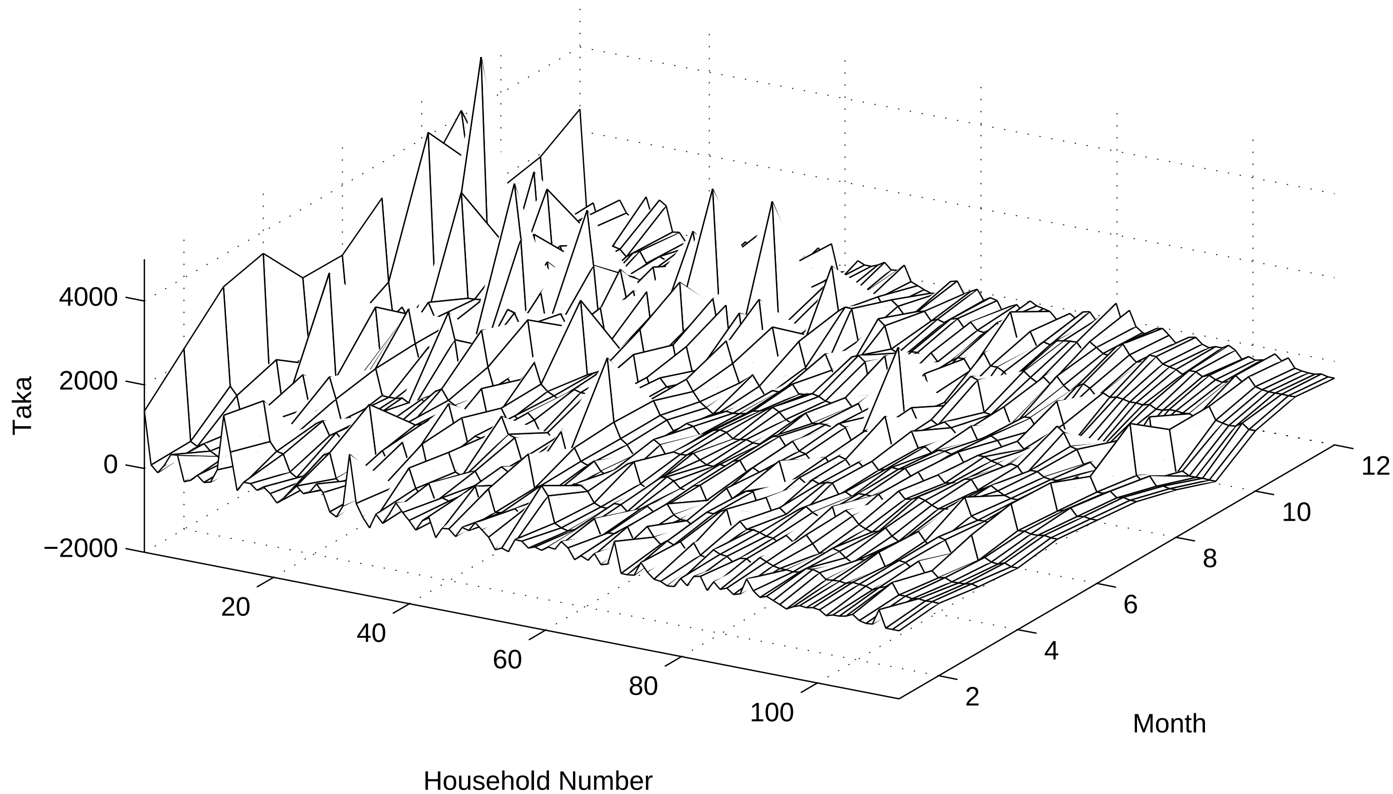



Figure 2b. Comovement of household revenue (deviations from village average): Village B

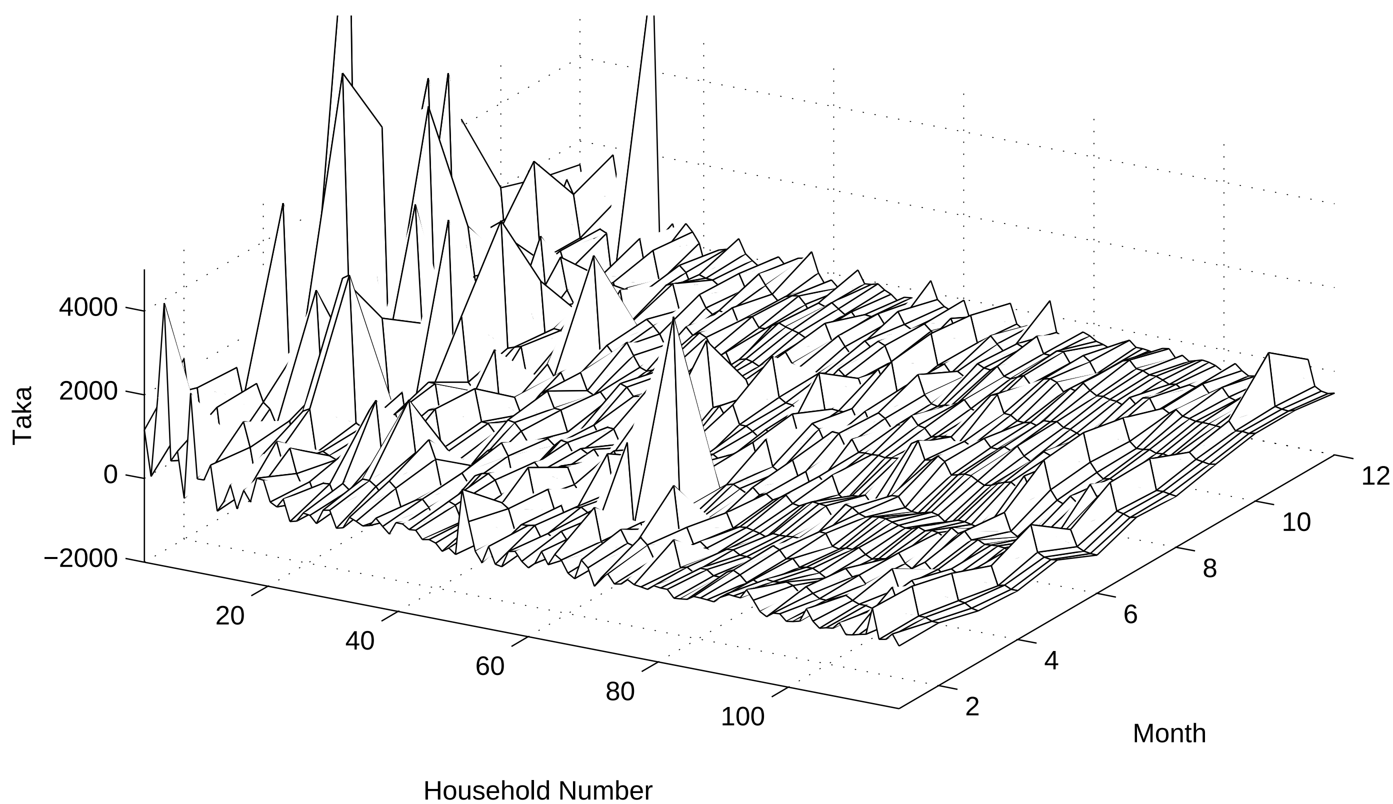


Figure 3a. Comovement of household consumption (deviations from village average): Village A

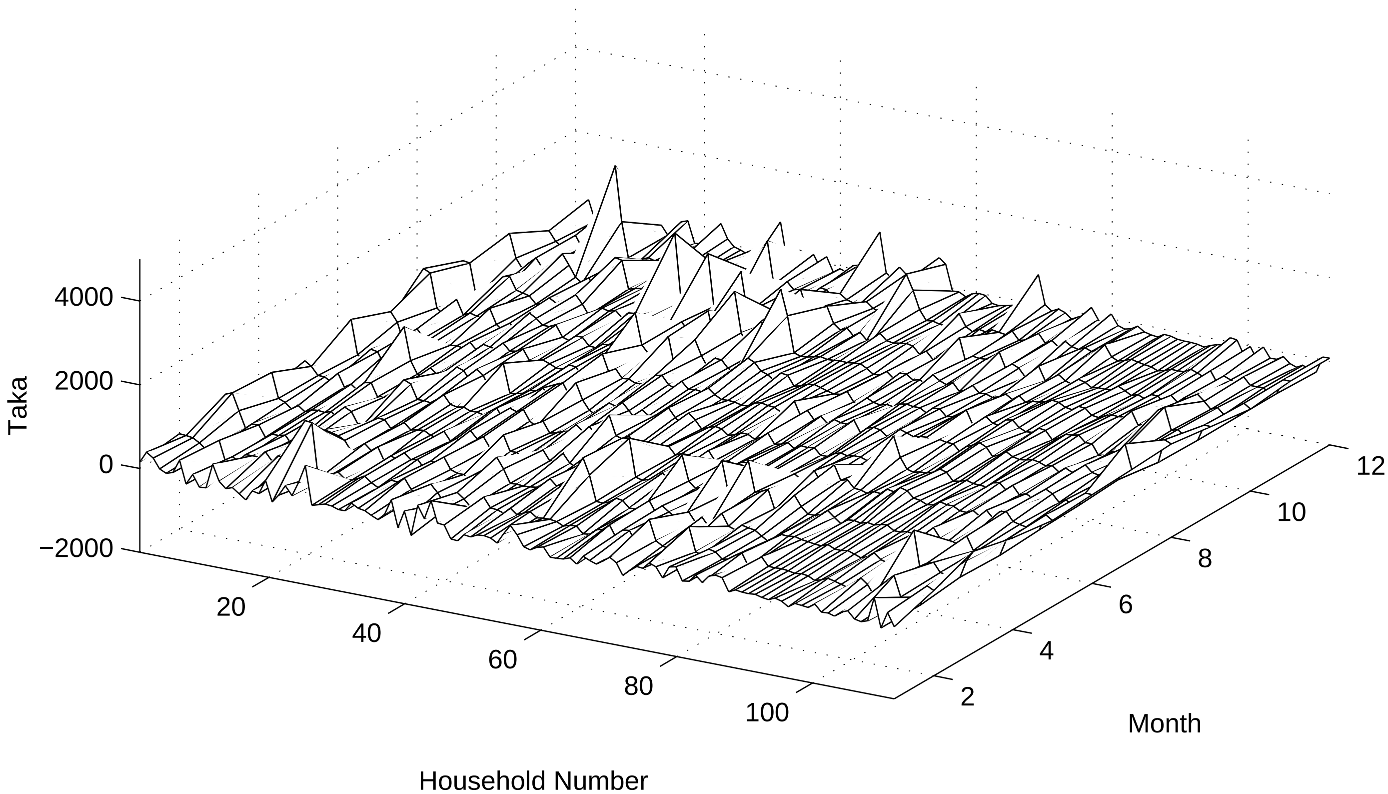



Figure 3b. Comovement of household consumption (deviations from village average): Village B

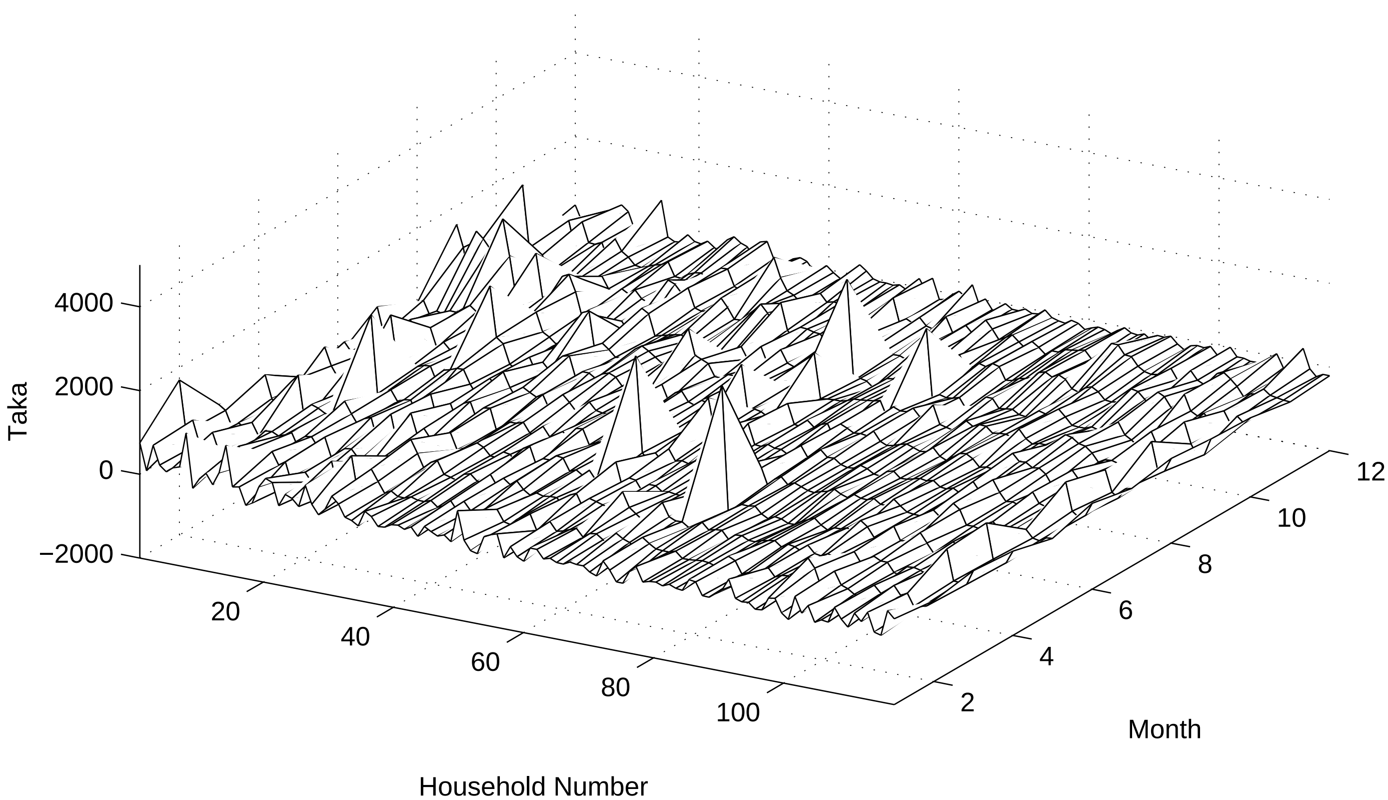


Figure 4a: CARA Utility
Vulnerability Coefficients with 90% Confidence Intervals, Village A

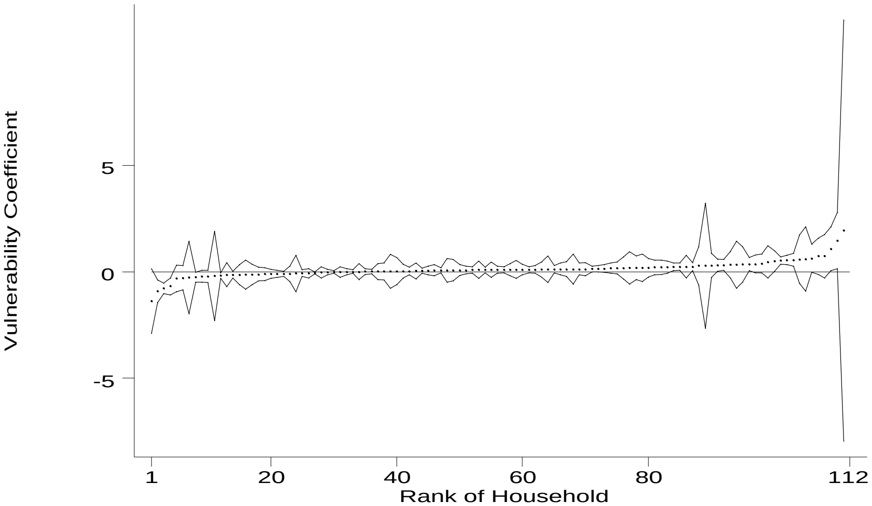



Figure 4b: CARA Utility
Vulnerability Coefficients with 90% Confidence Intervals, Village B

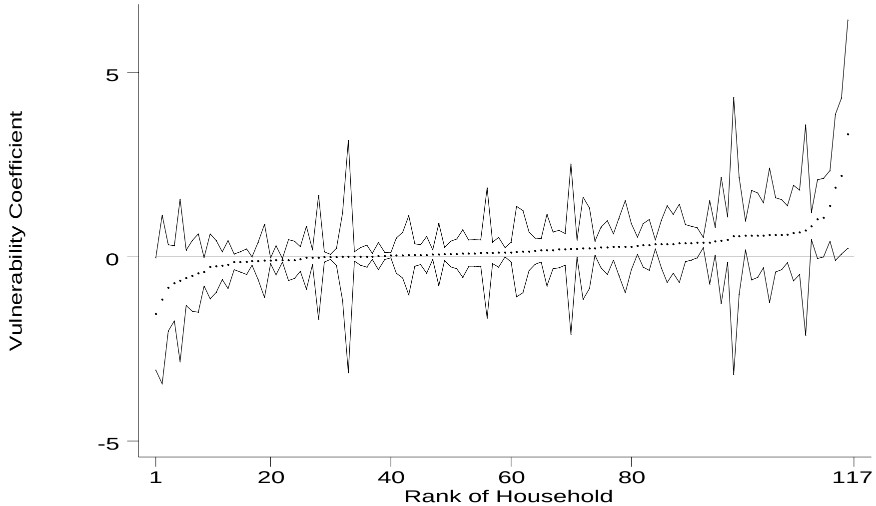



Figure 4c: CRRA Utility
Vulnerability Coefficients with 90% Confidence Intervals, Village A

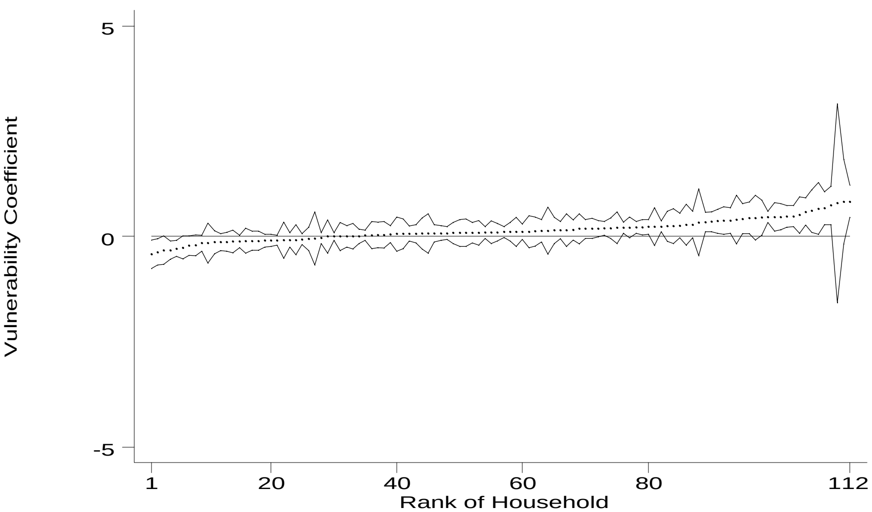
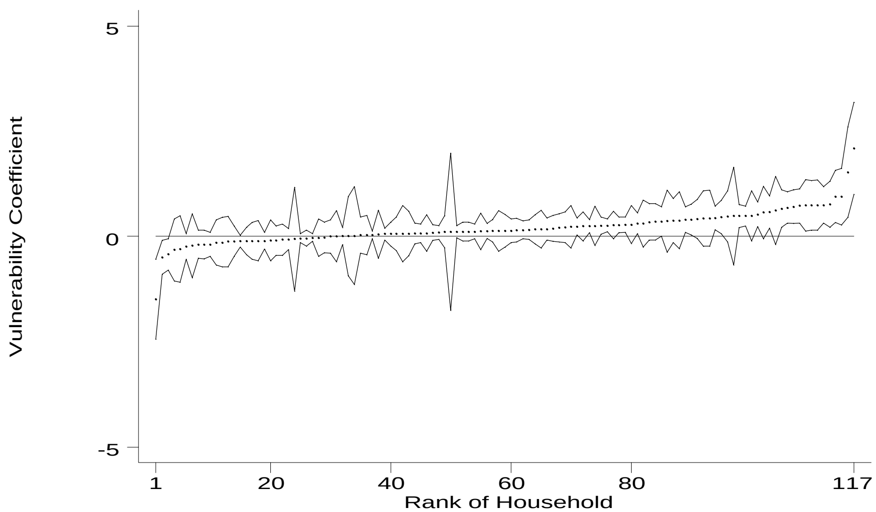



Figure 4d: CRRA Utility
Vulnerability Coefficients with 90% Confidence Intervals, Village B



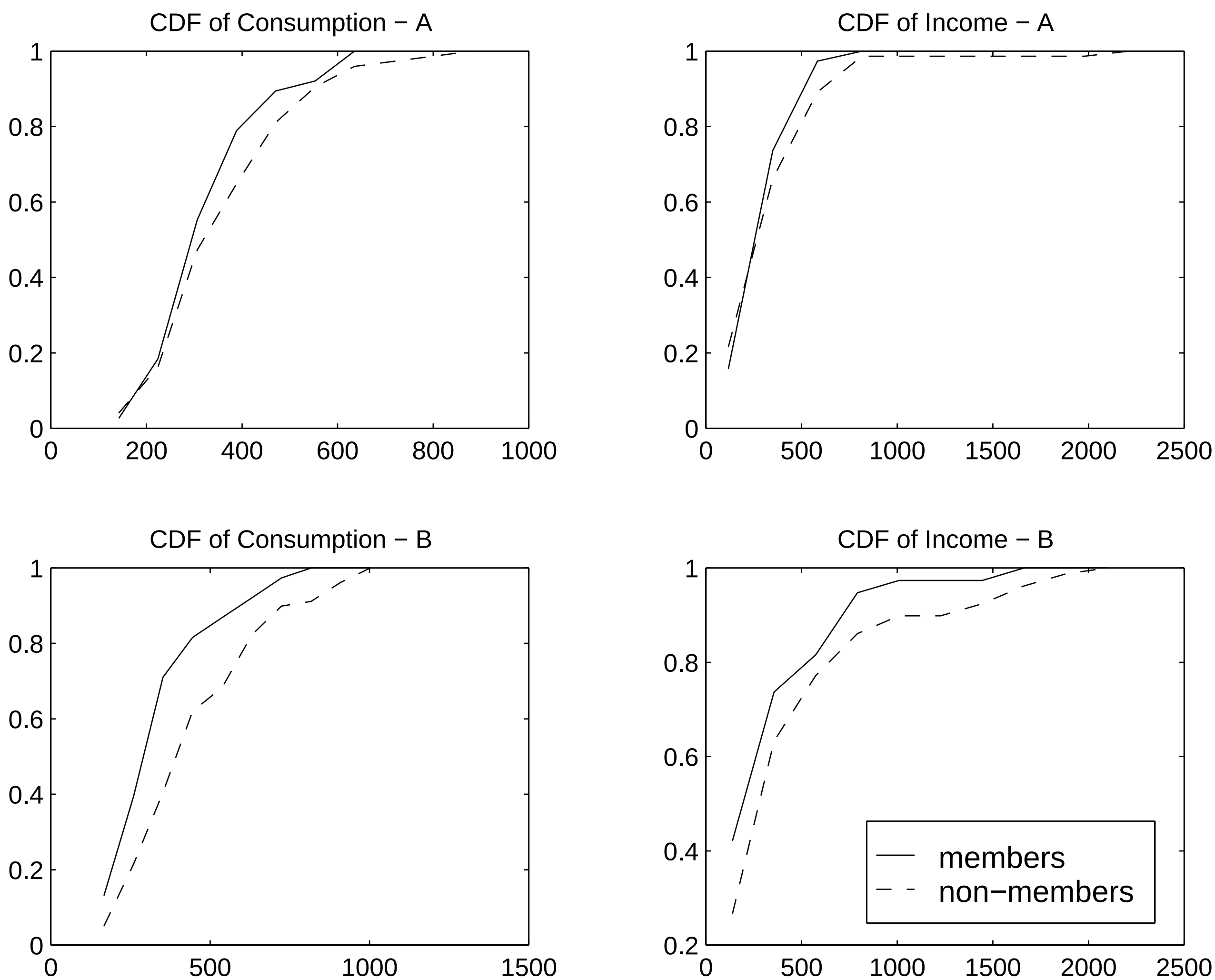



FIGURE 5: Poverty and Microcredit Membership

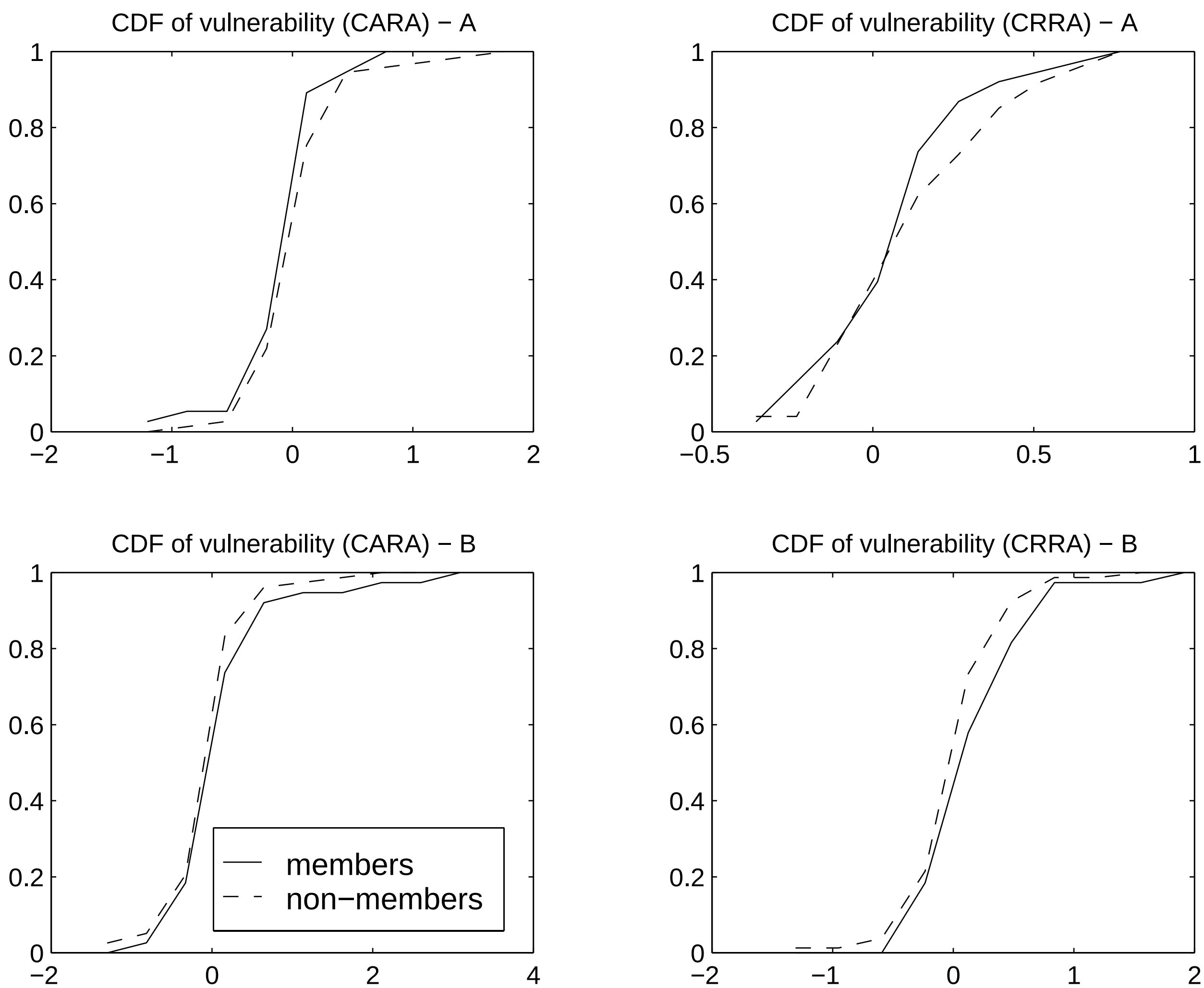



FIGURE 6: Vulnerability and Microcredit Membership

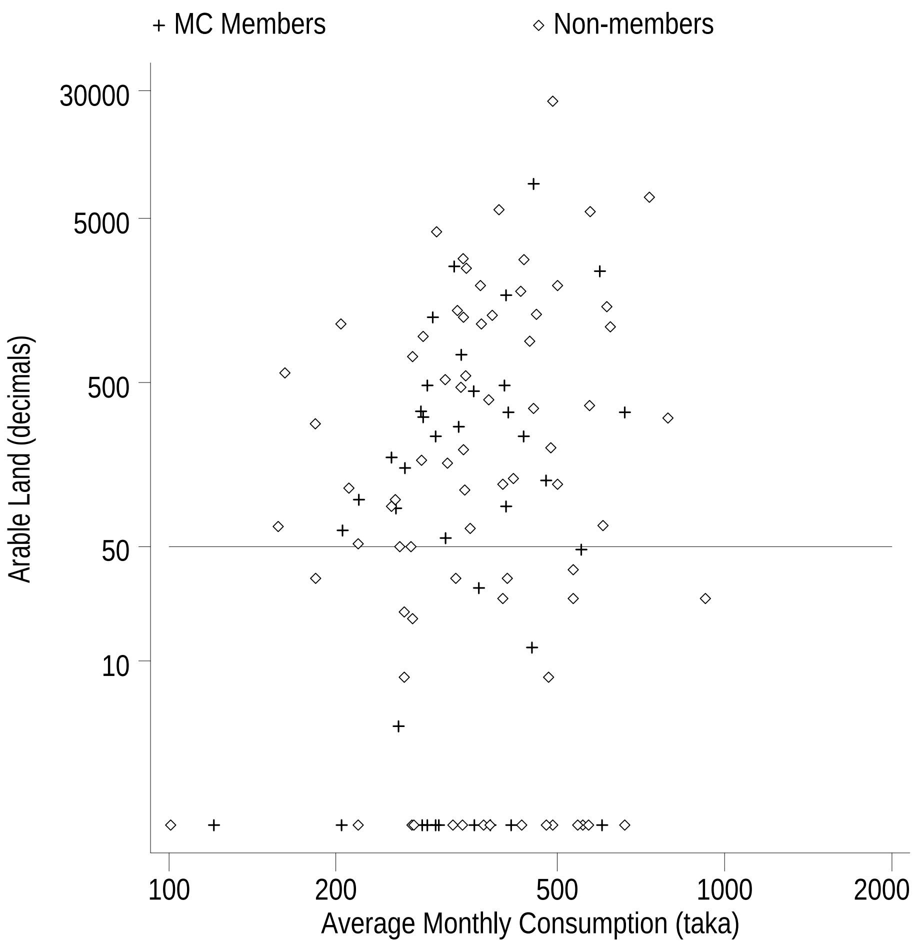



Figure 7a. Microcredit, Land and Consumption: Village A

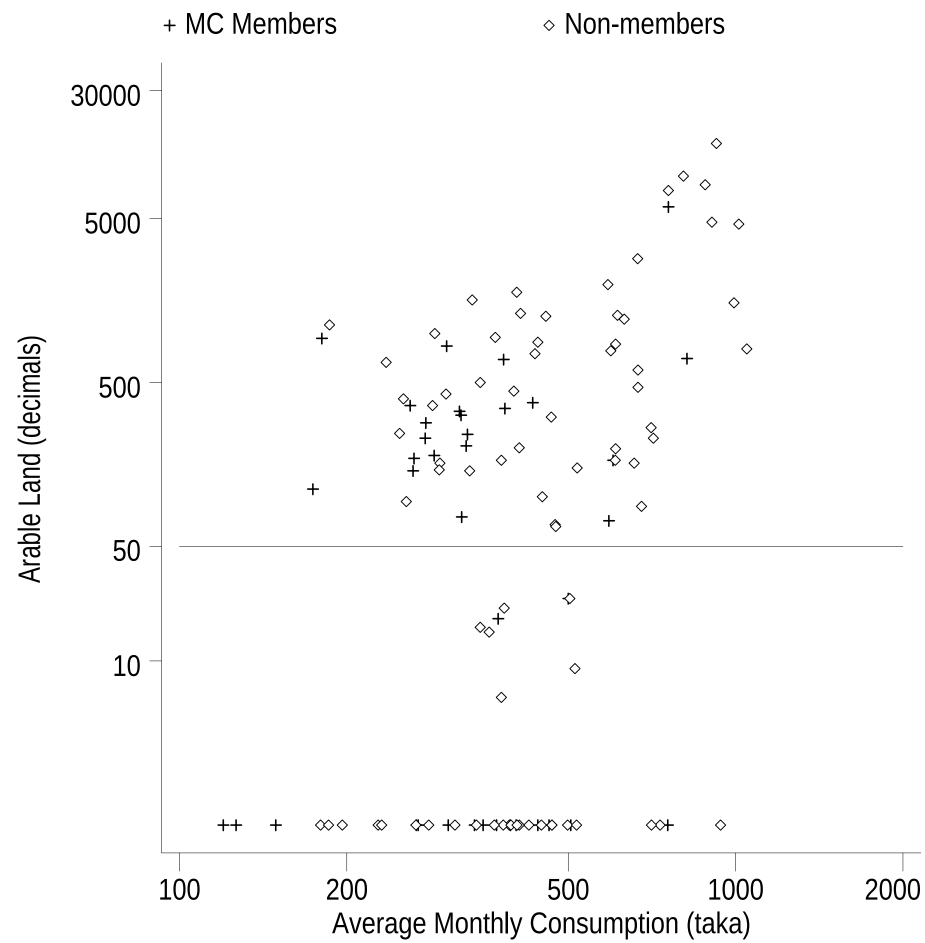



Figure 7b. Microcredit, Land and Consumption: Village A