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Does Microcredit Reach the Poor and Vulnerable? Evidence From Northern Bangladesh[1]

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Abstract

The Grameen Bank's success in Bangladesh has made microcredit the hot new idea for reducing poverty. This paper uses panel data from two Bangladeshi villages to test if loan recipients are poorer and more vulnerable than non-recipients. Poverty is measured by levels of consumption. Vulnerability is measured as fluctuations in consumption (associated with inefficient risk sharing). We find that loan recipients are poorer than non-recipients in both villages, but are more vulnerable than non-recipients only in the richer and more diversified village. Though microcredit programs target the landless, there is substantial leakage to the landed. Landlessness is not significantly associated with either poverty or vulnerability, but female headship is. Female headed households may be a more appropriate target group for anti-poverty credit programs.

JEL Classification Codes: O12, I32, C14.

Keywords: Microcredit, poverty, risk sharing, targeting.

1 Introduction

Microcredit has become "the world's hot idea for reducing poverty," according to the New York Times [13]. The Grameen Bank in Bangladesh is seen as the flagship for this anti-poverty movement, and Bangladesh as the hub of microcredit. Estimates suggest that lending programs including Grameen assist more than 6 million Bangladeshi families or 30 million people. One quarter of Bangladesh's population has a family member with access to small loans (Financial Times, [8]).

There is a long and sordid history of subsidized credit intended for the poor being politically manipulated and diverted to the rich and powerful (see Adams, Graham and Pischke [1]). But Grameen and the modern microcredit movement claims to be different. Grameen targets the landless, restricts its loans to women, and is squeaky clean.[1] Grameen claims to reach the poorest and most vulnerable, yet this claim has never been carefully tested.

We use data from two villages in Northern Bangladesh and ask if the households that join microcredit programs are poorer and more vulnerable than those that do not.[2] We define poverty in terms of levels of consumption and income and vulnerability in terms of fluctuations. Vulnerable households are those that are unable to smooth consumption in the face of fluctuations of income due to the seasonality of agricultural production, floods, illness, and other idiosyncratic shocks to the household resources. Vulnerability is an important determinant of household welfare, especially in the village economies studied here, where incomes are highly variable and consumption levels are low.

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 had only just begun to give loans in the two villages in $1991-92$, we can ignore issues of endogeneity for the most part.

We find that loan recipients are poorer than non-recipients in both villages, but are more vulnerable than non-recipients only in the richer and more

[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 [11])

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

diversified village. Though microcredit programs target the landless, there is substantial leakage to the landed. However, such leakage is not necessarily a bad outcome from the point of view of reaching the poor and vulnerable, since landlessness is not significantly associated with either poverty or vulnerability. On the other hand, female headed households appear to be both poorer and more vulnerable. Therefore, female headed households may be a more appropriate target group for anti-poverty credit programs.

A link is drawn here between two issues in development that have received recent attention. The first is the design and evaluation of microcredit programs, especially the Grameen Bank (see Morduch [11]). While there has been some recent research on microcredit's impact on the welfare of participating households in Bangladesh,[3] this is the first paper that empirically addresses the issue of who selects into microcredit programs.[4] The second strand of literature concerns tests of efficient risk sharing in village economies (see Townsend [16]). Microcredit programs may be correcting for inefficiencies in institutions and markets by providing safety nets to vulnerable households.[5] For instance, Grameen Bank's design comprises several insurance funds that provides repeat loans during hard times (see Shams [15]).

The rest of the paper is organized as follows. Section 2 describes the data and the general setting of the two villages. Section 3 reports our findings on the relationship between poverty and microcredit membership. Section 4 derives two measures of vulnerability, and describes our estimation strategy. Our main results linking vulnerability and membership in microcredit programs are reported here. Section 5 suggests alternative targeting strategies based on which observable household characteristics are associated with poverty and vulnerability. Finally, Section 6 concludes.

[3] For contrasting approaches to and results from the same World Bank dataset on the impact of microcredit on consumption levels in Bangladesh, see Pitt and Khandker [14] and Morduch[12]. Morduch[12] does find that microcredit programs play a role in reducing variation in consumption and labor supply across seasons but the World Bank data cannot address whether or not households that joined experienced more or less variability ex ante.

[4] For mechanism design models of how group selection excludes borrowers with a lower probability of success, see Armerandiz de Aghion [5] and Ghatak [9].

[5] For an illustration of how credit with contingencies can provide insurance, see Udry [17].

2 Data

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 northwest Bangladesh. Rajshahi district is close to the national average in terms of economic and health indicators (see UNICEF [18]). The villages were chosen to be neither extremely poor nor extraordinarily prosperous. Village B was chosen because it had experienced some development and economic diversification. 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. 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.[6] 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. 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 and better value. 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.[7] Each round corresponds roughly to a calendar month, with rounds starting in September 1991 for village A and October 1991 for village B. The data were collected

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

[7] 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.

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.[8] 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.

Table 2 reports summary statistics for the value of consumption, income, and revenues in taka for the two villages. The unit of observation is a household-round. Village B is wealthier than village A: average monthly consumption, income, and revenues are all higher in B. Average monthly income is approximately \$11 in village A and \$14 in village B, and average annual income is therefore approximately \$132 in village A and \$168 in village B.[9] Incomes and revenues are more volatile in B than in A. Since the coefficient of variation of consumption is lower than that of income or revenues for both villages, there appears to be some consumption smoothing by households.

Figures 1 through 3 plot 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

[8] 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 [16] which are based on a south Indian dietary survey.

[9] 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.

of the survey. Figure 4 plots the aggregate fluctuations of consumption and income in the two villages.

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 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 a third of all sampled households in each village had joined a microcredit program. 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.

3 Does microcredit reach the poor?

In this section, we first test if member households are poorer than non-member households in each village using tests for stochastic dominance described below. Then we check if microcredit members are indeed in the lower

[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 the following Sections.

quintiles of the poverty distribution. Finally, we test if our results remain the same if we control for other household characteristics that might influence the decision to join a microcredit program.

We measure poverty crudely by levels of (per adult equivalent) consumption. Consumption is a better indicator of household welfare in these villages than income. For instance, certain households receive meals and gifts in kind from relatives, and so may have low income levels but moderately high consumption levels. For comparison though we also report our results for income levels.

3.1 First order Stochastic Dominance Tests

The tool that we adopt to address the question of whether microcredit reaches the poor is a test of first order stochastic dominance, developed by Anderson [4]. In fact, our question translates into checking whether microcredit members were poorer (in terms of the 1991-92 transactions data) than non-members. Instead of looking at specific moments of the distribution of consumption for members and non-members, however, we prefer to take a more general approach and use the concept of stochastic dominance. In particular, we ask whether the distribution of 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.[12] 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:

$$F_N(c) \leq F_M(c), \;\; F_N(c_i) \neq F_M(c_i) \text{ for some } i, \;\; \forall c \in C. \tag{1}$$

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

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

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 (1) translates into the following hypothesis test:

$$H_0 : I_f(p^N - p^M) = 0 \text{ against } H_1 : I_f(p^N - p^M) \leq 0. \tag{2}$$

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.[13]

3.2 Results

We plot density comparisons of average consumption and income in Figure 7A and 7B. For both villages, and more so for village B, the density distribution for non-members is shifted to the right. The non-parametric tests in Table 5 show that the distribution of consumption for non-members first order stochastically dominates the distribution for members in both villages. Microcredit members are significantly poorer than non-members in consumption and income terms in both villages (using a 10% significance level) and more so in village B.

Probit regressions of microcredit membership on average consumption in column 3 of Table 12 go 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 will give a household a 6% higher probability of receiving a loan on average. Controlling for other household characteristics, however, microcredit's effectiveness in reaching the poor in village A disappears (see columns $4-6$ of Table 12). Low average consumption is still significantly associated with receiving loans in village B.

Since a third of the sampled households had received loans by 1995, microcredit would have succeeded in (almost perfectly) targeting the poor if all

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

the member households were at the bottom two quintiles of the distribution of average monthly consumption for the sample. But the data reveals 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 poor.

In summary then, microcredit members are slightly poorer than non-members in both villages, with a stronger and more robust 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 very small, so it is very unlikely to overturn the result of our stochastic dominance tests.

4 Does microcredit reach the vulnerable?

In this section we first present the theoretical framework, estimation strategy and results for RS vulnerability, our measure of vulnerability that is based on deviations from full risk sharing. Then we discuss an alternative measure of vulnerability based on what proportion of average consumption a household would be willing to give up for a certainty equivalent bundle. We refer to this second measure as CE vulnerability.

4.1 RS Vulnerability

4.1.1 Theoretical Derivation

A long literature starting with Wilson [19] and Diamond [7] 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,[14] 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,[15] 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, define the regression specification that we use to estimate RS vulnerability parameters for all households, and examine the question of whether microcredit does reach the most vulnerable households, in the specific sense defined here.[16]

Consider an economy with N households who live for T dates. At each date t uncertainty is represented by a vector θ_t of shocks. Components of θ 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 consumption $c^h(s_t)$ and $l^h(s_t)$ denote the 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:

$$\sum_{h=1}^{N} \lambda^h \sum_{t=1}^{T} \beta^{t-1} \sum_{s_t} prob(s_t) \cdot u^h(c^h(s_t), l^h(s_t)) \qquad (3)$$

subject to resource constraints for each history s_t:

$$\sum_h c^h(s_t) \leq C(s_t) \qquad (4)$$

$$\sum_h l^h(s_t) \leq L(s_t) \qquad (5)$$

where $C(s_t)$ and $L(s_t)$ denote aggregate consumption and leisure in the village contingent on the history s_t. The λ^h parameters in equation (3) denote the Pareto weights attached to each household h.[17] The maximization is also

[14] An incomplete list would include storage, sale and purchase of various assets, borrowing and lending, informal transfers within kinship networks.

[15] In particular, we assume that preferences are time-separable, agents are weakly risk averse and discount the future at the same rate, and there is no private information.

[16] Much of this section follows Deaton [6] , pages 372-383, and Townsend [16] closely.

[17] 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 in our setup.

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 one considers the case in which agents' preferences are separable across consumption and leisure, one obtains for all households h and for all states s_t (after taking logarithms):

$$\ln \mu^h(c^h(s_t)) = \ln \xi(s_t) - \ln \lambda^h - (t-1)\ln \beta - \ln(prob(s_t)) \tag{6}$$

where $\mu^h(\cdot)$ denotes the marginal utility of consumption and $\xi(s_t)$ is the multiplier associated with equation (4).[18] Taking first differences over time allows us to eliminate the term involving the Pareto weight λ^h. For all households h and for all states s_t:

$$\Delta \ln \mu^h(c^h(s_t)) = \Delta \ln \xi(s_t) - \Delta \ln(prob(s_t)) - \ln \beta \equiv \kappa(s_t) \tag{7}$$

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 CARA utility function:[19]

$$u^h\left(c^h(s_t), l^h(s_t)\right) = -\frac{1}{\sigma} n^h(s_t)\left[\exp\left(-\sigma\frac{c^h(s_t)}{n^h(s_t)}\right) + \exp(-\sigma\frac{l^h(s_t)}{n^h(s_t)})\right] \tag{8}$$

where $n^h(s_t)$ is the (age-sex adjusted) number of male adult equivalents in the household at time t. Equation (7) then specializes to the following for

[18] We just focus on consumption.

[19] The general implication that household consumption variables should comove holds generally for any concave utility function.

all households h:[20]

$$\Delta\left(\frac{c_t^h}{n_t^h}\right) = -\frac{1}{\sigma}\kappa_t \tag{9}$$

Equation (9) constitutes the basis of our estimation strategy. It basically implies that if full risk-sharing is in place, then changes in per-adult-equivalent consumption over time should comove across households. In other words, household consumption should only be affected by aggregate fluctuations in the village, and not be influenced by idiosyncratic shocks to the household's own income or resources. On the other hand, a household that is not particularly well-insured against idiosyncratic risk will display a certain sensitivity of changes in consumption to changes in its own individual income or resources. We take this as our definition of RS vulnerability, and our estimation strategy focuses on identifying individual households within each village that are more vulnerable to idiosyncratic risk.

In what follows, we also estimate RS vulnerability parameters using a CRRA utility specification, to make sure that our results are not affected by the choice of functional form. Using the following utility function:

$$u^h\left(c^h(s_t), l^h(s_t)\right) = \frac{1}{1-\gamma} n^h(s_t)\left[\left(\frac{c^h(s_t)}{n^h(s_t)}\right)^{1-\gamma} + \left(\frac{l^h(s_t)}{n^h(s_t)}\right)^{1-\gamma}\right], \tag{10}$$

we derive the counterpart to equation (9):

$$\Delta \ln\left(\frac{c_t^h}{n_t^h}\right) = -\frac{1}{\gamma}\kappa_t \tag{11}$$

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 (9) and (11). 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.

[20] We drop the s_t notation and use a time subscript only, as the sharing rule 7 holds for every history and therefore also for the realized sequence of shocks.

4.1.2 Estimation strategy

Our strategy for estimating RS vulnerability parameters is quite simple. We estimate a linear regression model based on equation (9), aimed at identifying vulnerable households in the sense described above. Having estimated a measure of RS vulnerability for each household, we can then analyze the relationship between this and subsequent microcredit membership, much in the same way that we looked at the relationship between poverty and membership.

Equation (9) suggests the following regression equation:

$$\Delta\tilde{c}_t^h = \alpha^h \Delta\tilde{y}_t^h + \phi_t \cdot MD_t + \varepsilon_t^h. \qquad (12)$$

where $\tilde{c}_t^h \equiv c_t^h / n_t^h$ denotes per-adult-male equivalent consumption of household h in month t, $\tilde{y}_t^h$ 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 error term ε_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. $\sigma_{ht}^2 = \sigma_h^2 \ \ \forall\ t$;
2. $\sigma_{h,ts} = 0 \ \ \forall\ t \neq s$;
3. $\sigma_{hk,ts} = 0 \ \ \forall\ h \neq k,\ t \neq s$;
4. $\sigma_{hk,tt} = 0 \ \ \forall\ t, h, k$.

The first assumption on heteroskedasticity is motivated by the results of several tests[21] 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 (12) via FGLS, postulating that the individual household variance depends on several observable characteristics (such as landholdings or household size) in the following way:

$$\sigma_h^2 = \sigma^2 \cdot \exp(\beta' z_h).$$

[21] 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 (12) has been estimated numerous times in the literature on tests of the complete markets hypothesis, in 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 (9) implies that α 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.

However, 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 α^h parameter for each household h. A household is defined to be RS 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 RS vulnerability.

Finally, the counterpart to equation (12) for the CRRA case is the following:

$$\Delta \ln \widetilde{c}_t^h = \alpha^h \Delta \ln \widetilde{R}_t^h + \phi_t \cdot MD_t + \varepsilon_t^h, \tag{13}$$

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.

4.1.3 Results

RS Vulnerability Estimates One immediate indication that risk sharing is incomplete in these two villages is seen in Table 6. If risk sharing were complete, all households in a village should experience their lowest consumption of the year in the same month. The table indicates however that different households experience their worst months at different points during the year. Thus there is definitely room for risk sharing.

For our RS vulnerability estimates, regression (12) and its CRRA counterpart (13) were estimated separately for each village. The distribution of the estimated $\widehat{\alpha}^h$ in each case is depicted in Figure 8. The mean of the RS 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. Roughly one quarter of the estimated parameters is negative. This is hard to interpret in the framework of a full risk-sharing model, lacking a specification for an alternative model. One could explain such negative parameters with the presence of unexpected shocks in a permanent income model. If income rises but less than expected, consumption may actually decrease in order to properly adjust savings.

It is also hard to establish a metric to rank households according to their level of RS vulnerability. The theoretical framework only offers some guidance to determine whether or not full risk sharing holds for a given household, but one needs an alternative model to interpret the size of a significantly positive RS 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, α^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 RS 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 α^h parameter will increase from zero to unity.[22]

With CARA utility, we found 19 RS vulnerable households in village A and 18 in village B, using a 10% statistical significance level.[23] With CRRA utility, we found 36 RS vulnerable households in both villages, at the 10% significance level. One would perhaps expect to observe more vulnerable households in these village economies. However, the standard errors of our estimated $\widehat{\alpha}^h$ tend to be large because we have only 12 rounds of observations for each household. Taking this fact into account, there is quite strong evidence to reject full risk sharing in both villages. For the remainder of this paper, since our focus is on the distribution of vulnerability within each village, we use the point estimates $\widehat{\alpha}^h$ as our measure of individual RS vulnerability.

RS Vulnerability and Microcredit Membership We now turn to the relationship between RS vulnerability and microcredit membership. A membership variable is defined for each household as a dummy variable that takes

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

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

value one if any household member has joined any microcredit organization by 1995, and zero otherwise. We proceed much in the same way as for poverty. Firstly, we perform first order stochastic dominance tests to determine whether members are more RS vulnerable than non-members. Secondly, we report the results of a probit estimation with microcredit membership as the dependent variable, to see whether an increase in RS vulnerability significantly increases the probability of being a microcredit member.

Table 7 contains the first order stochastic dominance test results. The density and CDF of RS vulnerability, for members and non-members, is also plotted in Figure 9. There is some evidence that non-members are more vulnerable than members in village A, whereas in B members appears to be more vulnerable. This result holds regardless of the type of utility function employed to estimate RS vulnerability. Therefore, it seems that microcredit does reach more vulnerable households in village B, whereas it is less successful at doing so in A.

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 lessen the degree of vulnerability of a household, or leave it unaltered. Then the timing problem biases our results in the direction less favourable to microcredit. Given that some members may appear to us less vulnerable than they actually were, we may underestimate microcredit's effectiveness at reaching the vulnerable in village B. Luckily, 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 can quantify the extent to which microcredit reaches RS vulnerable households in B (and does not in A) using a similar argument to that of Section 3. 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 RS vulnerability in 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 situated in the top two quintiles of the RS vulnerability distribution in village A, whereas 53% of all members are in the two highest quintiles of the distribution in B.[24] Again, given the possibility of bias in village B, these numbers indicate that microcredit does quite a good job in village B, whereas for A the degree of mistargeting of the most vulnerable is substantial.

Finally, the probit regression of microcredit membership on RS vulnerability (with CARA utility) is reported in Table 12. The results are inconclusive, especially for village A. However, there is some evidence that microcredit reaches the most RS vulnerable in B. In column (1), the coefficient associated to 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, poverty, and CE vulnerability, although the p-value grows larger.

4.2 CE Vulnerability

If households are risk averse, then they would prefer to avoid fluctuations in consumption. We use an alternative measure in which vulnerability is identified directly with consumption smoothing. Consider a particular household h, with observed consumptions c_t^h for at each month $t = 1...12$. Denote this household's average monthly consumption by $\overline{c}^h$. Define c^{h*} as the household's certainty equivalent consumption:

$$u(c^{h*}) = \sum_{t=1}^{12} \frac{1}{12} u(c_t^h)$$

This household would be willing to give up $\overline{c}^h - c^{h*}$ of its average consumption for the certainty equivalent. Define CE vulnerability (for a particular utility function) as $\frac{\overline{c}^h - c^{h*}}{\overline{c}^h}$, the proportion of its average consumption that the household would be willing to forego for the certainty equivalent.

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

In practice, CE vulnerability was calculated using a range of values for the coefficient of absolute (or relative) risk aversion. For CRRA, Ligon [10] estimates the relative risk aversion parameter γ to lie in the interval [0.7, 1.3]. To be on the safe side, we use $\gamma \in \{0.5, 1, 2\}$. For CARA, we use the median average monthly consumption in each village to impute a value of the absolute risk aversion parameter σ that is consistent with a relative risk aversion in the range [0.5, 2].

4.2.1 Results

Households in both villages seem to be substantially vulnerable even using this alternative measure of vulnerability. In both villages, the median CE vulnerability (using CARA) is 0.069, which means that the median household is willing to give up 7% of its expected monthly consumption to be able to smooth consumption across time. The top quintile is a level of CE vulnerability of 15% in both villages, and the maximum level of CE vulnerability is roughly 40% in A and 34% in B. These are fairly large portions of expected consumption.

As for the relationship between CE vulnerability and microcredit membership, we report the results of the first order dominance tests in Table 8; the densities and CDFs for members and non-members are drawn in Figure 10. The results of the probit regression of membership on CE vulnerability are reported in Table 12.

The first order stochastic dominance tests confirm what we find using RS vulnerability. There is strong evidence that non-members are more CE vulnerable than members in village A (in a first order dominance sense). This result holds regardless of the utility function and of the imputed values for the coefficients of risk aversion. For village B, again there is evidence that microcredit members are more vulnerable than non-members, especially if we use a CRRA framework. Thus both the RS and the CE measures of vulnerability yield the same pattern of results. In terms of the possible timing bias for village B discussed earlier, again such a bias would only strengthen our conclusion that microcredit does reach the most vulnerable in B.

How successful or unsuccessful is microcredit in each village? We repeat the same exercise we performed for poverty and RS vulnerability. We divide the distribution of CE vulnerability in quintiles: under perfect targeting, all microcredit members should fall in the two highest quintiles. Using CARA utility, only 29% of microcredit members in A come from the top two quintiles, whereas for B the same statistic is 40%.[25] Therefore, our CE vulnerability results strengthen the impression that at least in A the degree of mistargeting of the most vulnerable households is quite high. In B, microcredit is moderately successful, but our figure may be biased down because of the timing issue.

Finally, Table 12 supports the conclusions of the first order dominance tests. Column (5) indicates that, even controlling for poverty, RS vulnerability and other household characteristics, an increase in CE vulnerability by 10% raises the probability of being a microcredit member by about 12% in village B, and lowers it by about 16% in A. These results are statistically significant and stable across specifications.

5 Targeting Strategies

In this Section, we ask if there are any observable characteristics associated with poverty and vulnerability in the two villages, and whether microcredit programs systematically succeed or fail at selecting households with these characteristics. 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.

Table 9 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 female headed households, larger households, households with a smaller output from the cash crop paan (betel leaf), and households that have uneducated heads in village A. In village B, poverty is associated with households that have uneducated heads and more children. In addition, the point estimates suggest that poverty is also associated with female headedness and smaller cash crops in B, although the p-values make these estimates significant only at the 15% significance level.

The orders of magnitude for some of these associations are high. Column (5) of Table 9 shows that the predicted monthly consumption for male headed households in village A exceeds the predicted monthly consumption for female headed households by 90 taka which is nearly a quarter of the

[25]With CRRA utility, we obtain even more striking results: only 29% of microcredit members in A come from the top two quintiles, whereas in B we have 50% of members coming from the top of the CE vulnerability distribution.

village average. A household head with some education increases his or her household consumption one average by 72 taka in village A and 115 taka in village B with respect to a household where the head has no education. The link between poverty and number of children in village B is intriguing: an extra child reduces average consumption by 34 taka.[26]

It is harder to find observable household characteristics that are readily associated with vulnerability. Table 10 and 11 present the results of regressing RS and CE vulnerability on household characteristics for both villages. The RS vulnerability coefficients come from the estimates of α^h based on equation (12), which assume a common coefficient of absolute risk aversion across households. The CE vulnerability estimates assume a common coefficient of absolute risk aversion $\sigma = 1$ and are based on the procedure described in section 4.2.

Female heads are more vulnerable in village B, under both definitions of vulnerability. Table 10 indicates that, keeping other characteristics constant, female headed households have a predicted RS 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 RS vulnerability coefficients is 0.19 in village B. From Table 11 we see that female headship is also associated with CE vulnerability, though the effects are smaller. On average female headed households are willing to give up 3% more of their average consumption than male headed households for the certainty equivalent in village B. By way of contrast, note that the median household is willing to give up 7% of its expected monthly consumption to be able to smooth across time.

RS vulnerability is also significantly associated with smaller households and those with older heads in village A, and with households with lower levels of consumption in village B (from Table 10). The latter result indicates that poorer households also tend to be more vulnerable, at least in terms of being unable to share out some of their idiosyncratic risk. This makes intuitive sense, and suggests that household welfare should be evaluated not just in terms of levels, but also in terms of their ability to insure against risk. On the other hand, Table 11 indicates that our measure of CE vulnerability is significantly positively associated with average monthly consumption, and hence that richer households are more CE vulnerable. This result is

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

surprising, but it could be simply a consequence of the fact that we use median consumption in the village to get a range of values for the coefficient of absolute risk aversion.

Female headed, smaller, older and poorer households are all naturally associated with being less able to smooth consumption in the face of idiosyncratic income fluctuations in village economies. Female headed households are marginalized and may have less access to kinship and other risk sharing networks. Smaller and older households are less able to put in labor in times of adverse income shocks. And a possible reason that more vulnerable households are poorer than others is that because of the lack of risk sharing capabilities they must undertake safer and lower return projects than other households. What is surprising, however, is the relative weakness of these partial correlations between household vulnerability and household characteristics.[27] Targeting vulnerable households seems a lot more difficult than targeting the poor for anti-poverty programs.

Microcredit programs miss several crucial household categories in both villages. Female headship does not significantly affect a household's probability of joining a microcredit program in either village (from Table 12) but female headship is significantly associated with poverty in village A and vulnerability in village B. Households with younger heads have a higher probability of joining microcredit programs (from Table 12, column 6), while we know from Table 10 that households with older heads are more likely to be RS vulnerable. A household with an uneducated head is not significantly more likely to join in village A, (from Table 12) but this household category is significantly poorer in both villages. In village B, households with uneducated heads have a 19% higher chance of joining, and there microcredit is reaching the right group. Notice that in village A each additional member boosts a household's likelihood of joining by 11%. But larger households are both poorer and less vulnerable in village A.

Finally we consider the one targeting criterion that microcredit programs in both villages 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 2 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 households that joined

[27] The adjusted R^2 of the regression with RS vulnerability as the dependent variable is at best 0.07.

in both villages were ineligible by the landholding criterion.[28] Notice that among the sampled households, there were more landless households in each village than microcredit members; so it is not as if these programs have reached all the households in the their target group and are now extending their credit to the non-target group.

How good a criterion is landlessness for targeting the poor and vulnerable anyway? Scatterplots of arable landholdings and average consumption and income levels in Figures 5 and 6 show that the relationship between poverty and landlessness is weak. Controlling for other household characteristics, landlessness has no significant influence in predicting average consumption levels in Table 9 in both villages. Further, landlessness is not associated with either RS or CE vulnerability in both villages. 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 by itself not a cause for alarm.

The above analysis does suggest and alternative target group: female headed households. These households have lower average consumptions and incomes than male headed households in both villages (from Table 4). This category is poorer in village A and more vulnerable in village B controlling for other characteristics (from Tables $9, 10$ and 11). 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 this is the appropriate target group: female headed households are the only ones for whom begging is socially sanctioned in village A. In addition, Amin [3] reports that the negative consequences of female headship are perpetuated through the generations: 27% of female headed households in the sample report a separated or divorced daughter, compared with less than 5% in male headed households. Therefore, it may be worthwhile for microcredit programs to try to target female headed households more actively.

[28] These may be overestimates. Households may have either split or sold land after 1992 prior to joining microcredit programs. Further, our sample is quite small. Interestingly though, Morduch [12] finds that $20-30\%$ of borrowers are ineligible using a much larger sample.

6 Conclusion

This paper uses panel data from two Bangladeshi villages to test if loan recipients are poorer and more vulnerable than non-recipients. 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.

We measure poverty by levels of consumption. Vulnerability is measured as fluctuations in consumption. Two distinct measures of vulnerability were used: RS vulnerability which is derived from tests of full risk sharing, and CE vulnerability which is a simple welfare measure of consumption smoothing. We find that loan recipients are poorer than non-recipients in both villages, but are more vulnerable than non-recipients only in the richer and more diversified village. Though microcredit programs target the landless, there is substantial leakage to the landed. Landlessness is not significantly associated with either poverty or vulnerability, but female headship is. Therefore, female headed households may be a more appropriate target group for anti-poverty programs.

One of the aims of this paper is to link the study of risk sharing and efficiency in village economies with the design of anti-poverty credit programs. The existence of RS vulnerable households in these two villages is a sign of market and institutional failures. Anti-poverty programs should be designed to include these households. Credit may be an inappropriate strategy to reach vulnerable groups however: the same forces that make some households vulnerable may also make them greater risks for small loan providers. There may be a tradeoff between reaching the poorest and most vulnerable and repayment rates. Of course, if Grameen Bank has indeed come up with an innovative mechanism to lend without collateral, specifying a poorer more vulnerable target group may not lower the repayment rates at all. Either way, the intensity of targeting the poor and vulnerable depends partly on the welfare function used. There is more to microcredit provision for poverty reduction than repayment rates.

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).

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Table 1.
Primary Occupation of Household Head

	Percentage of Households	
	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

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

Table 2a.
Summary Statistics for Village A*
(112 Households x 12 Rounds = 1344 observations)

	Mean	Std. Dev.	CV
Food Consumption	324.00	272.55	0.84
All Consumption	388.38	313.89	0.81
All Income	429.69	658.25	1.53
All Revenue	537.23	743.12	1.38

Table 2b.
Summary Statistics for Village B*
(117 Households x 12 Rounds = 1404 observations)

	Mean	Std. Dev.	CV
Food Consumption	351.73	337.32	0.96
All Consumption	466.93	420.49	0.90
All Income	537.62	1000.14	1.86
All Revenue	681.84	1088.85	1.60

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 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[a]	38[b]
Non-members	74	79
Members of ASA	12	3
Members of BRAC	16	19
Members of Grameen	10	17

[a] 14 microcredit members were landless in 1992 in Village A.

[b] 17 microcredit members were landless in 1992 in Village B. In Village B, one HH is a member of both BRAC and Grameen.

Table 4a.
Consumption and Income by household category, Village A*

Category	*Variable*	*Mean*	*Std. Dev.*	*CV*
Landless (arable land <= 0.5 acres)	Consumption	396.77	289.02	0.73
	Income	355.20	385.84	1.09
Landed	Consumption	384.30	240.41	0.63
	Income	465.91	656.38	1.41
Female-headed	Consumption	331.27	229.31	0.69
	Income	227.93	312.43	1.37
Male-headed	Consumption	392.27	258.68	0.66
	Income	443.45	595.68	1.34
Uneducated HH Head	Consumption	368.38	252.66	0.69
	Income	379.60	456.85	1.20
Educated HH Head	Consumption	415.97	261.29	0.63
	Income	498.81	718.56	1.44
Members of Microcredit NGO	Consumption	359.06	193.92	0.54
	Income	369.28	495.28	1.34
Non-members	Consumption	404.61	285.23	0.70
	Income	463.15	625.59	1.35

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 4b.
Consumption and Income by household category, Village B*

Category	*Variable*	*Mean*	*Std. Dev.*	*CV*
Landless (arable land <= 0.5 acres)	Consumption	402.30	310.61	0.77
	Income	428.90	536.88	1.25
Landed	Consumption	504.14	342.59	0.68
	Income	600.20	1009.58	1.68
Female-headed	Consumption	369.34	292.33	0.79
	Income	271.21	401.54	1.48
Male-headed	Consumption	475.73	337.01	0.71
	Income	561.62	897.59	1.60
Uneducated Head	Consumption	386.79	270.53	0.70
	Income	372.04	564.09	1.52
Educated Head	Consumption	561.52	376.32	0.67
	Income	733.04	1099.65	1.50
Members of Microcredit NGO	Consumption	382.38	263.32	0.69
	Income	456.81	530.05	1.16
Non-members	Consumption	500.69	353.86	0.71
	Income	569.88	972.68	1.71

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.

Poverty and Microcredit Membership

Tests of Stochastic Dominance

Consumption Comparision

Village A Members minus Non-members	(t-statistics)		Village B Members minus Non-members	(t-statistics)	
-0.0142	-0.3841		0.0809	1.5387	*
0.0220	0.2944		0.1795	2.0403	**
0.0797	0.7983		0.3055	3.0947	***
0.1408	1.5347	*	0.1955	2.1300	**
0.0839	1.1450		0.1849	2.1447	**
0.0156	0.2750		0.0983	1.4125	*
0.0405	1.2581		0.0750	1.4247	*
0.0270	1.0226		0.0886	1.8924	**
0.0135	0.7198		0.0380	1.2170	

Income Comparision

Village A Members minus Non-members	(t-statistics)		Village B Members minus Non-members	(t-statistics)	
-0.058	-0.736		0.155	1.691	*
0.075	0.807		0.104	1.117	
0.082	1.508	*	0.044	0.539	
0.014	0.720		0.087	1.396	*
0.014	0.720		0.075	1.425	*
0.014	0.720		0.075	1.425	*
0.014	0.720		0.050	1.060	
0.014	0.720		0.038	1.217	
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 10%

**Statistically significant at 5%

***Statistically significant at 1%

Table 6a.
Worst Months, Village A

Month	Number of households with lowest consumption of the year
September,1991	9
October	14
November	15
December	11
January,1992	9
February	8
March	15
April	2
May	6
June	9
July	6
August	8
Total	112

Table 6b.
Worst Months, Village B

Month	Number of households with lowest consumption of the year
October,1991	4
November	18
December	10
January,1992	7
February	11
March	9
April	5
May	7
June	10
July	11
August	9
September	16
Total	117

Table 7.
RS Vulnerability and Microcredit Membership
Tests of Stochastic Dominance

CARA Utility Function (sigma=1)

Village A Members minus Non-members	(t-statistics)		Village B Members minus Non-members	(t-statistics)	
-0.0137	-0.7248		-0.0256	-0.9957	
-0.0011	-0.0333		-0.025	-0.6214	
-0.0148	-0.3964		-0.0209	-0.2652	
-0.036	-0.4255		-0.0965	-1.2233	
0.115	1.4184	*	-0.0405	-0.9241	
0.0422	0.9324		-0.027	-0.7477	
0.0411	1.2669		-0.0398	-1.2679	
0.0274	1.0297		-0.0263	-1.4389	*
0.0137	0.7248		-0.0263	-1.4389	*

CRRA Utility Function (gamma=1)

Village A Members minus Non-members	(t-statistics)		Village B Members minus Non-members	(t-statistics)	
-0.0142	-0.3841		-0.0127	-0.6965	
0.091	1.7712	*	-0.0127	-0.6965	
0.0071	0.0844		-0.038	-1.217	
-0.0242	-0.2463		-0.031	-0.3886	
0.1152	1.2194		-0.1552	-1.6909	*
0.1387	1.6689	*	-0.1083	-1.7449	*
0.0697	1.056		-0.0137	-0.5337	
0.0284	0.5535		-0.0137	-0.5337	
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 10%

**Statistically significant at 5%

***Statistically significant at 1%

Table 8.
CE Vulnerability and Microcredit Membership
Tests of Stochastic Dominance

CARA Utility Function (sigma=1)

Village A Members minus Non-members	(t-statistics)		Village B Members minus Non-members	(t-statistics)	
0.0576	0.6137		-0.1332	-1.5632	*
0.1415	1.5078	*	-0.0959	-0.9748	
0.1387	1.6689	*	0.0143	0.1585	
0.1636	2.2318	**	0.0173	0.2110	
0.0953	1.6747	*	0.0077	0.1130	
0.0541	1.4595	*	0.0740	1.2347	
0.0541	1.4595	*	0.0486	0.8811	
0.0270	1.0226		0.0233	0.4680	
0.0135	0.7198		-0.0400	-1.2810	

CRRA Utility Function (gamma=1)

Village A Members minus Non-members	(t-statistics)		Village B Members minus Non-members	(t-statistics)	
0.0989	1.1072		-0.1479	-1.8553	**
0.1323	1.3266		-0.1516	-1.5450	*
0.1529	1.7492	*	-0.1825	-1.9381	**
0.1771	2.3644	**	-0.1006	-1.1802	
0.0953	1.6747	*	-0.0197	-0.2644	
0.0676	1.6394	*	-0.0187	-0.2681	
0.0270	1.0226		-0.0556	-0.9655	
0.0270	1.0226		-0.0283	-0.6047	
0.0135	0.7198		-0.0137	-0.5337	

The columns report the differences between the CDF of Members and Non-members, at several points. Under the null Hp. 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 10%
**Statistically significant at 5%
***Statistically significant at 1%

Table 9.
Linear Regressions of Poverty on Household Characteristics.
(Dependent Variable: Average Consumption)

	(1)	(2)		(3)	(4)	(5)
			Female-headed, Village A	**-94.408**	**-89.461**	**-89.796**
Female-headed	**-73.009**	**-72.436**		(0.02)	(0.06)	(0.02)
	(0.01)	(0.02)	Female-headed, Village B	**-56.768**	**-55.549**	**-52.653**
				(0.12)	(0.16)	(0.15)
			Landless, A	**-28.201**	**30.986**	**24.720**
Landless	**-30.624**	**-18.812**		(0.40)	(0.38)	(0.47)
	(0.21)	(0.46)	Landless, B	**-31.364**	**-67.453**	**-39.799**
				(0.32)	(0.04)	(0.19)
			Age of HH head, A		**-0.166**	
Age of HH Head		**0.594**			(0.89)	
		(0.56)	Age of HH head, B		**0.764**	
					(0.53)	
			HH Structure , A		**-6.521**	
Household Structure		**1.633**			(0.60)	
		(0.86)	HH Structure , B		**13.710**	
					(0.20)	
			Household Size, A		**-18.926**	**-32.263**
Household Size		**-7.042**			(0.14)	(0.00)
		(0.41)	Household Size, B		**-7.047**	**5.189**
					(0.53)	(0.54)
			Uneducated Head, A		**-48.954**	**-72.417**
Uneducated HH Head		**-90.546**			(0.15)	(0.03)
		(0.00)	Uneducated Head, B		**-117.82**	**-114.59**
					(0.00)	(0.00)
			Paan Production, A		**0.008**	**0.008**
Paan Production		**0.004**			(0.00)	(0.00)
		(0.02)	Paan Production, B		**0.005**	**0.004**
					(0.12)	(0.14)
			No. of Children, A		**-22.551**	**-11.291**
Number of Children		**-36.417**			(0.22)	(0.49)
		(0.00)	No. of Children, B		**-32.178**	**-34.315**
					(0.048)	(0.02)
			No. of Old People, A		**-41.598**	
Number of Old People		**-47.289**			(0.28)	
		(0.097)	No. of Old People, B		**-51.257**	
					(0.18)	
Adjusted R^2	**0.035**	**0.173**		**0.029**	**0.251**	**0.245**

P-values are in parentheses.

Table 10.
Linear Regressions of RS Vulnerability on Household Characteristics.
(Dependent Variable: RS Vulnerability)

	(1)	(2)
Female-headed	**0.195**	**0.107**
	(0.01)	(0.25)
Landless	**0.010**	**0.021**
	(0.87)	(0.78)
Age of HH Head		**0.004**
		(0.23)
Household Structure		**-0.018**
		(0.51)
Household Size		**-0.008**
		(0.76)
Uneducated HH Head		**0.008**
		(0.91)
Paan Production		**0.000**
		(0.81)
Number of Children		**0.006**
		(0.87)
Number of Old People		**0.018**
		(0.83)
Average Consumption		**-0.0002**
		(0.24)
Adjusted R^2	**0.023**	**0.011**

	(3)	(4)	(5)
Female-headed, Village A	**0.004**	**-0.243**	**-0.145**
	(0.97)	(0.09)	(0.23)
Female-headed, Village B	**0.338**	**0.330**	**0.352**
	(0.00)	(0.01)	(0.00)
Landless, A	**0.006**	**-0.037**	
	(0.94)	(0.73)	
Landless, B	**0.026**	**0.018**	
	(0.75)	(0.86)	
Age of HH head, A		**0.005**	**0.007**
		(0.22)	(0.03)
Age of HH head, B		**0.001**	**0.001**
		(0.71)	(0.66)
HH Structure , A		**-0.078**	
		(0.05)	
HH Structure , B		**-0.001**	
		(0.97)	
Household Size, A		**0.007**	**-0.037**
		(0.85)	(0.05)
Household Size, B		**0.013**	**0.017**
		(0.71)	(0.46)
Uneducated Head, A		**0.067**	
		(0.51)	
Uneducated Head, B		**-0.036**	
		(0.71)	
Paan Production, A		**0.000**	
		(0.43)	
Paan Production, B		**0.000**	
		(0.93)	
No. of Children, A		**-0.006**	
		(0.91)	
No. of Children, B		**-0.008**	
		(0.86)	
No. of Old People, A		**0.096**	
		(0.42)	
No. of Old People, B		**-0.070**	
		(0.54)	
Average Consumption, A		**0.0002**	**-0.0002**
		(0.61)	(0.50)
Average Consumption, B		**-0.0005**	**-0.0004**
		(0.045)	(0.07)
Adjusted R^2	**0.046**	**0.043**	**0.070**

P-values are in parentheses.

Table 11.

Linear Regressions of CE Vulnerability on Household Characteristics.

(Dependent Variable: CE Vulnerability)

	(1)	(2)
Female-headed	**0.001**	**0.010**
	(0.93)	(0.46)
Landless	**-0.002**	**0.002**
	(0.86)	(0.87)
Age of HH Head		**0.000**
		(0.85)
Household Structure		**0.000**
		(0.95)
Household Size		**-0.002**
		(0.62)
Uneducated HH Head		**0.016**
		(0.13)
Paan Production		**0.000**
		(0.59)
Number of Children		**0.001**
		(0.87)
Number of Old People		**0.003**
		(0.79)
Average Consumption		**0.0002**
		(0.00)
Adjusted R^2	**-0.009**	**0.202**

	(3)	(4)	(5)
Female-headed, Village A	**-0.021**	**-0.005**	**-0.007**
	(0.25)	(0.83)	(0.68)
Female-headed, Village B	**0.018**	**0.029**	**0.031**
	(0.27)	(0.10)	(0.04)
Landless, A	**0.010**	**0.004**	
	(0.48)	(0.79)	
Landless, B	**-0.012**	**0.009**	
	(0.40)	(0.53)	
Age of HH head, A		**0.000**	
		(0.43)	
Age of HH head, B		**0.000**	
		(0.99)	
HH Structure , A		**0.007**	
		(0.22)	
HH Structure , B		**-0.006**	
		(0.24)	
Household Size, A		**-0.007**	
		(0.23)	
Household Size, B		**0.004**	
		(0.42)	
Uneducated Head, A		**0.011**	**0.020**
		(0.49)	(0.13)
Uneducated Head, B		**0.019**	**0.014**
		(0.20)	(0.28)
Paan Production, A		**0.000**	
		(0.88)	
Paan Production, B		**0.000**	
		(0.54)	
No. of Children, A		**0.005**	
		(0.52)	
No. of Children, B		**-0.003**	
		(0.69)	
No. of Old People, A		**0.001**	
		(0.96)	
No. of Old People, B		**0.003**	
		(0.87)	
Average Consumption, A		**0.0002**	**0.0002**
		(0.00)	(0.00)
Average Consumption, B		**0.0002**	**0.0002**
		(0.00)	(0.00)
Adjusted R^2	**-0.005**	**0.201**	**0.233**

P-values are in parentheses.

Table 12.
Probit Regressions of Microcredit Membership on Vulnerability and Household Characteristics.
(Dependent Variable: Microcredit Membership)

	(1)	(2)	(3)	(4)	(5)	(6)
RS Vulnerability, Village A	**-0.074** (0.55)			**-0.123** (0.36)	**-0.083** (0.59)	**-0.065** (0.67)
RS Vulnerability, Village B	**0.124** (0.13)			**0.109** (0.20)	**0.103** (0.26)	**0.114** (0.20)
CE Vulnerability, A		**-0.985** (0.08)		**-1.530** (0.05)	**-1.664** (0.04)	**-1.626** (0.04)
CE Vulnerability, B		**-0.442** (0.36)		**1.335** (0.05)	**1.182** (0.095)	**1.258** (0.07)
Average Consumption, A			**-0.0006** (0.01)	**-0.0002** (0.48)	**0.0000** (0.96)	**0.0000** (0.91)
Average Consumption, B			**-0.0006** (0.00)	**-0.0009** (0.00)	**-0.0007** (0.04)	**-0.0007** (0.02)
Female-headed, A					**-0.094** (0.48)	
Female-headed, B					**0.068** (0.61)	
Landless, A					**-0.098** (0.38)	**-0.112** (0.30)
Landless, B					**-0.111** (0.254)	**-0.115** (0.23)
Age of HH head, A					**-0.010** (0.01)	**-0.011** (0.00)
Age of HH head, B					**-0.008** (0.07)	**-0.006** (0.097)
Household Size, A					**0.108** (0.01)	**0.114** (0.00)
Household Size, B					**-0.062** (0.14)	**-0.070** (0.08)
Uneducated Head, A					**0.055** (0.59)	**0.042** (0.68)
Uneducated Head, B					**0.178** (0.08)	**0.192** (0.05)
Paan Production, A					**-0.00002** (0.01)	**-0.00002** (0.01)
Paan Production, B					**0.000** (0.71)	**0.000** (0.65)
No. of children, A					**-0.173** (0.01)	**-0.175** (0.00)
No. of children, B					**0.102** (0.08)	**0.104** (0.07)
No. of Old people, A					**0.013** (0.92)	
No. of Old people, B					**0.059** (0.64)	
R^2	**0.01**	**0.01**	**0.04**	**0.07**	**0.19**	**0.19**

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

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

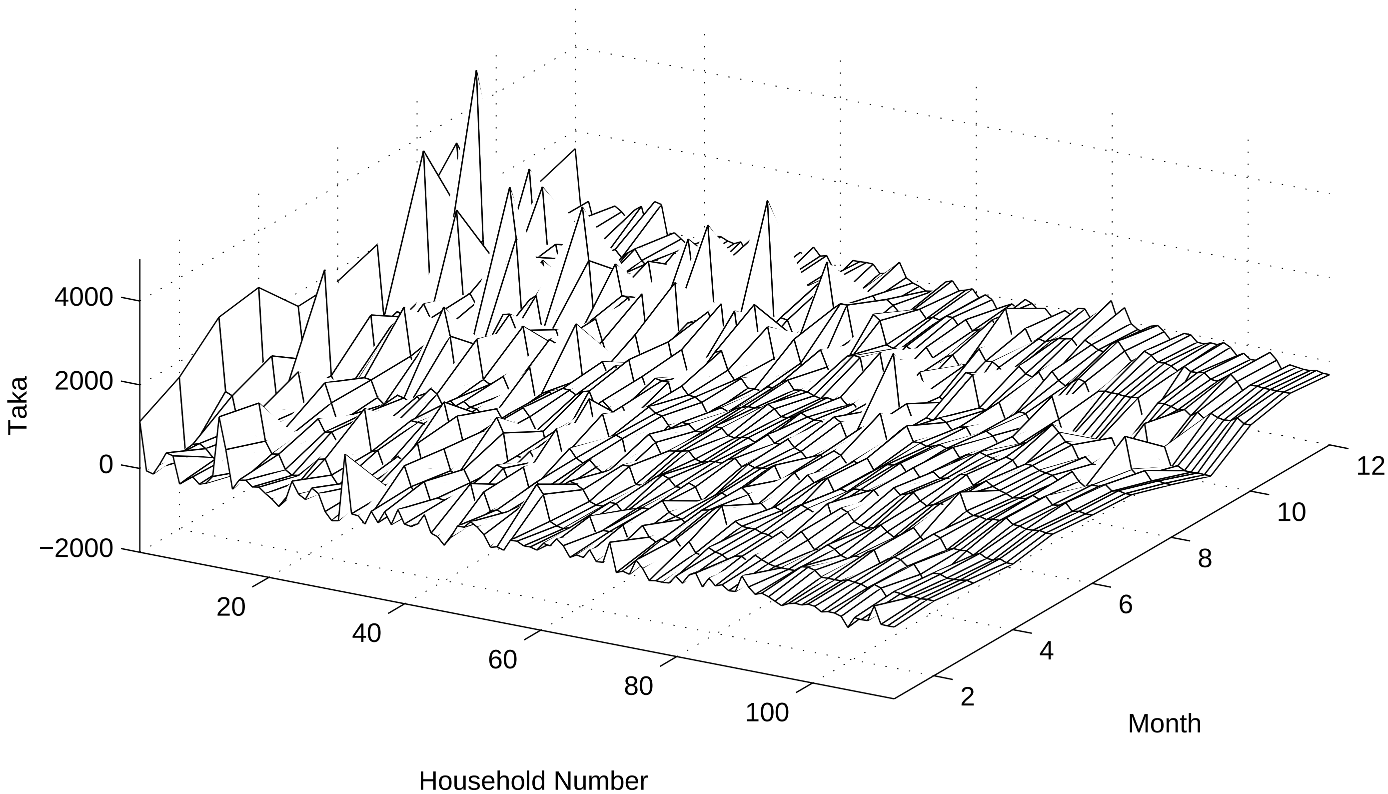


Figure 1b. Comovement of household income (deviations from village average): Village B

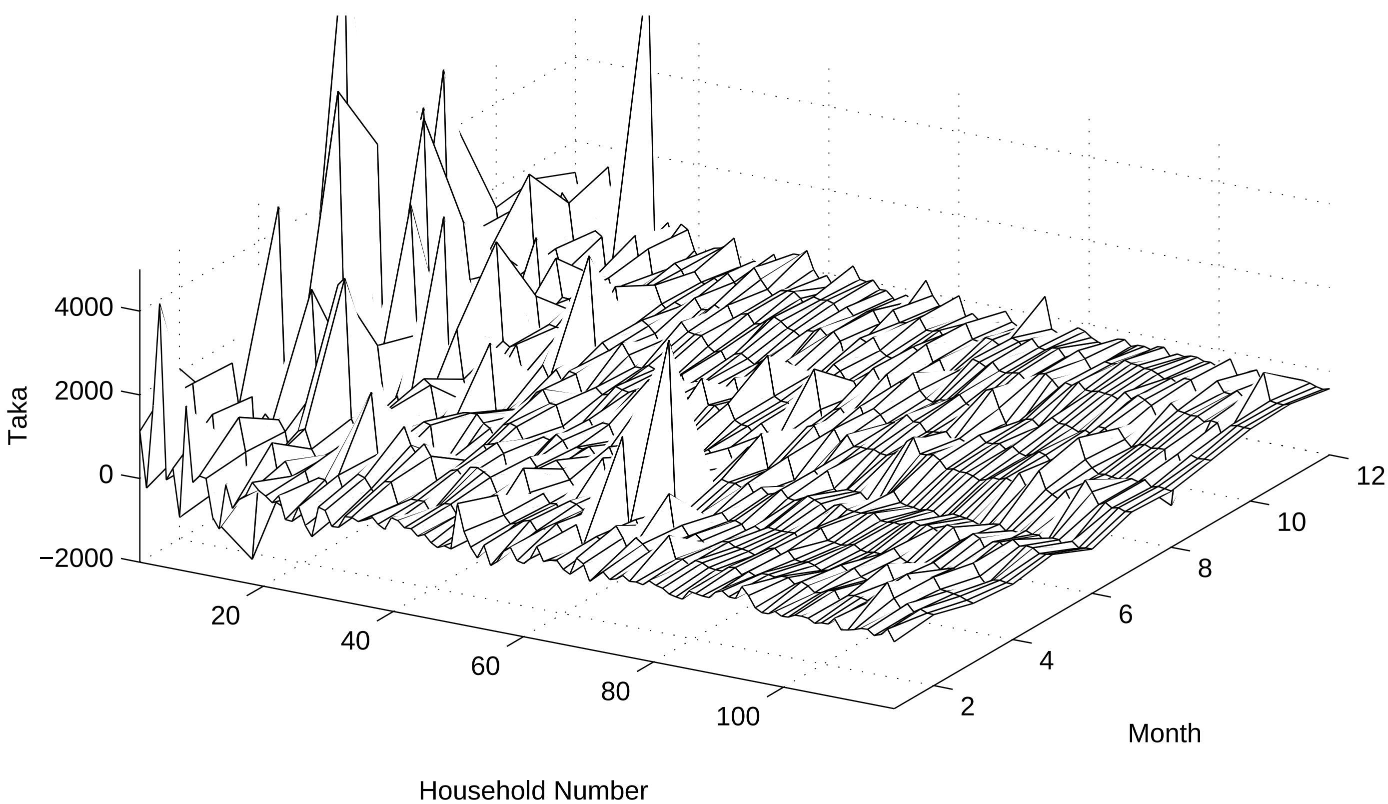


Figure 2a. Comovement of household revenue (deviations from village average): Village A

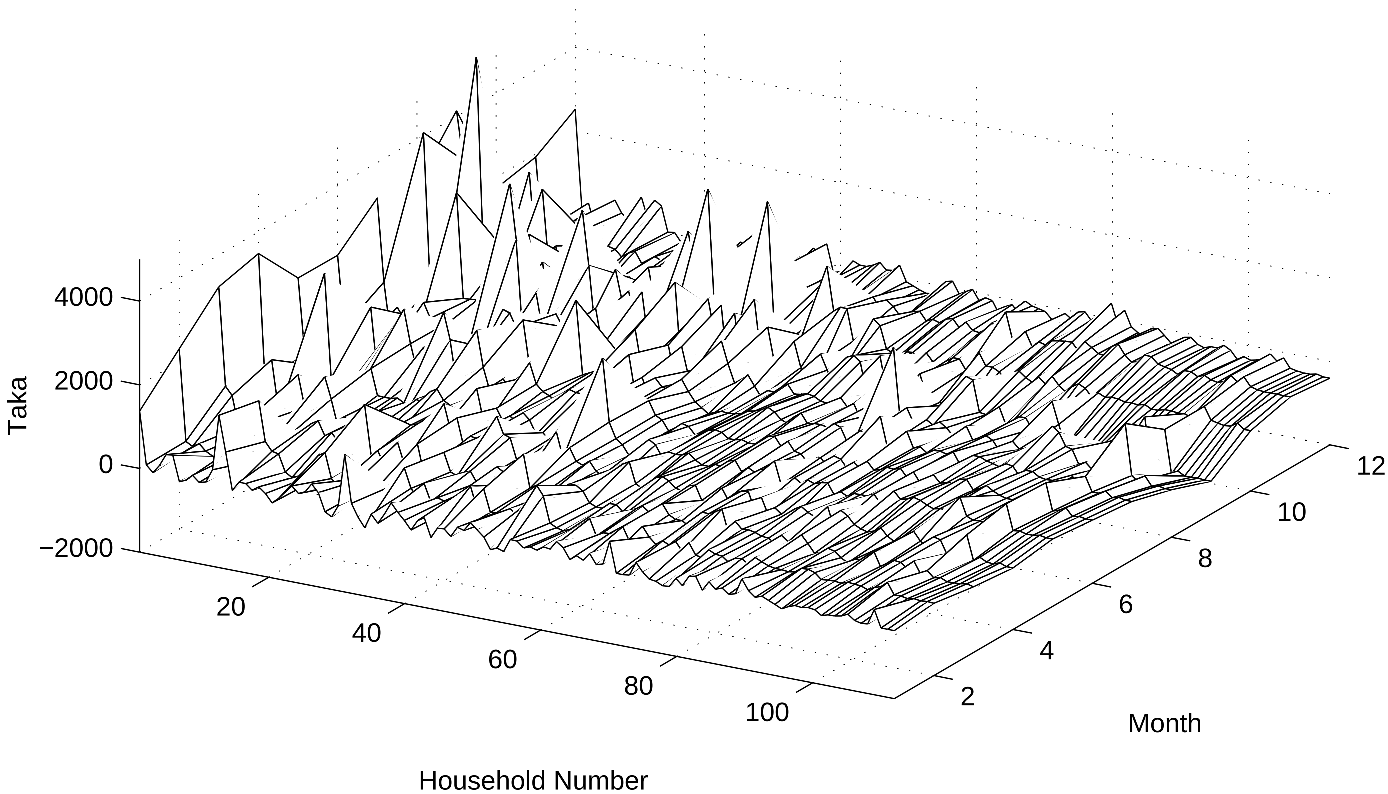


Figure 2b. Comovement of household revenue (deviations from village average): Village B

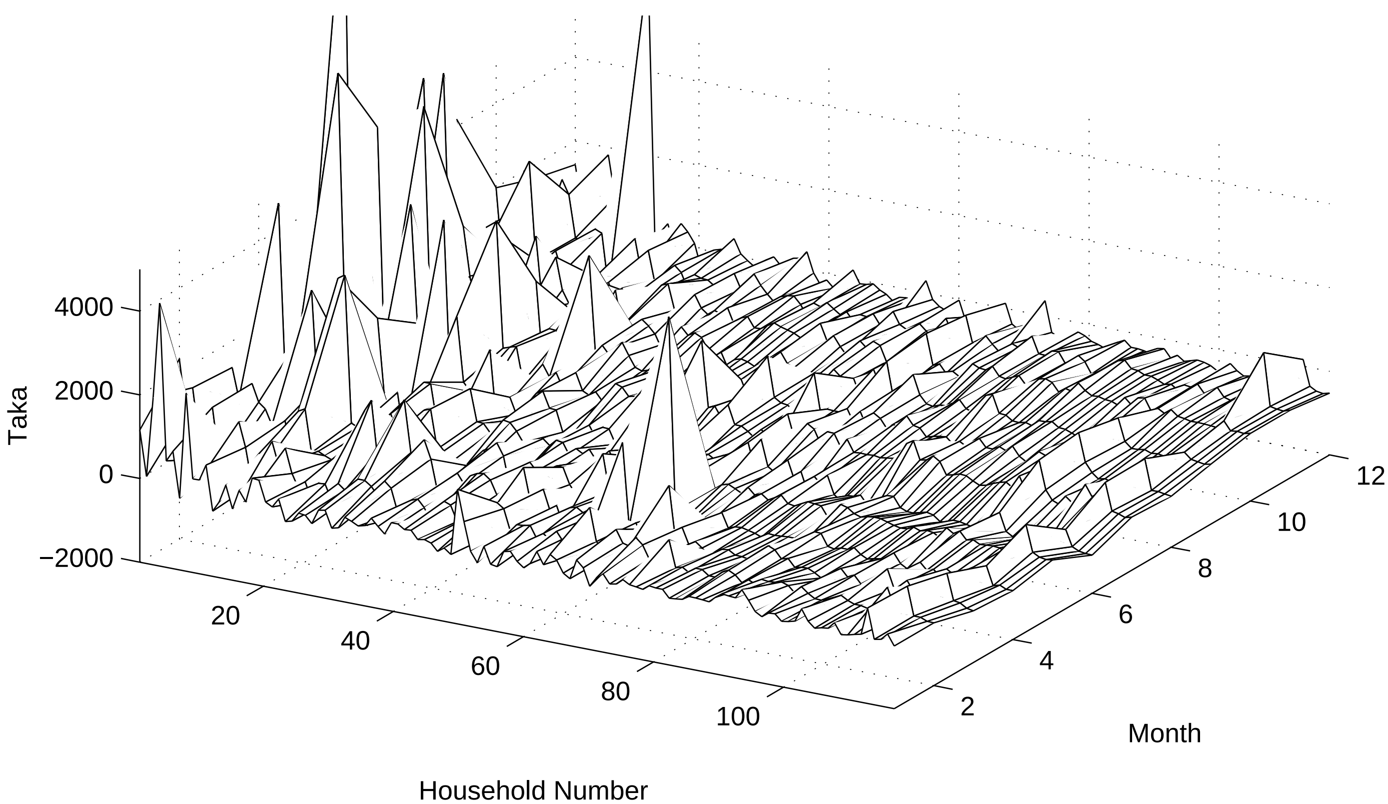


Figure 3a. Comovement of household consumption (deviations from village average): Village A

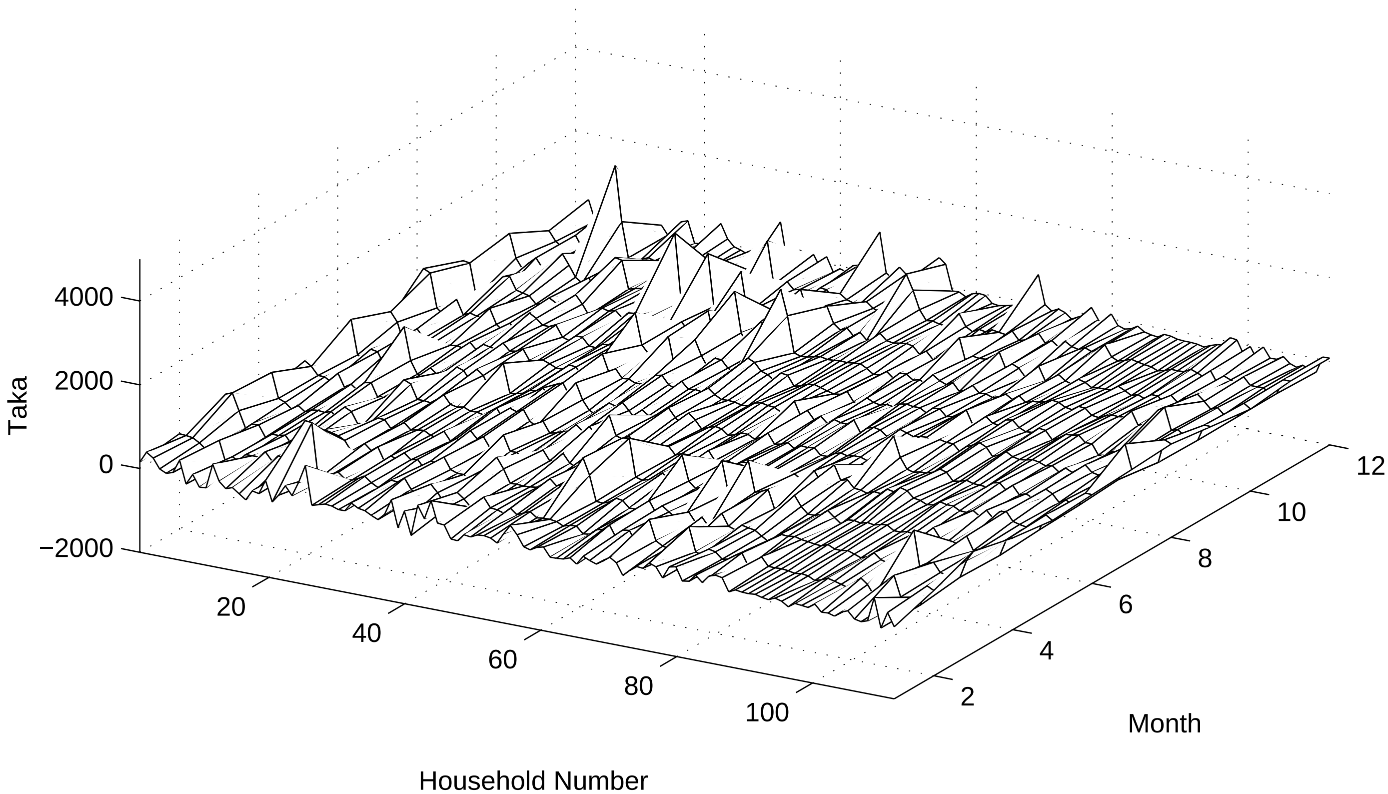


Figure 3b. Comovement of household consumption (deviations from village average): Village B

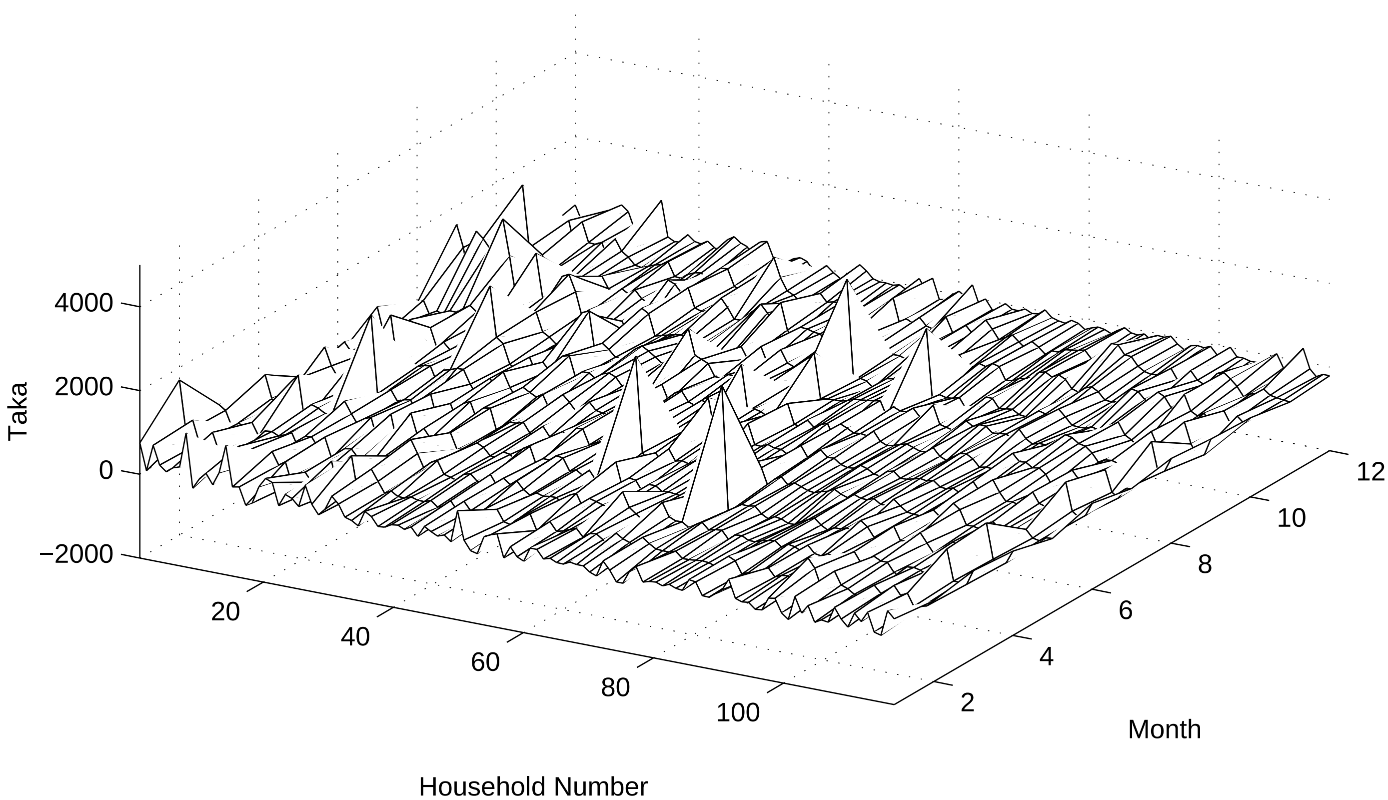


Figure 4a.
Fluctuations in Income and Consumption, Village A

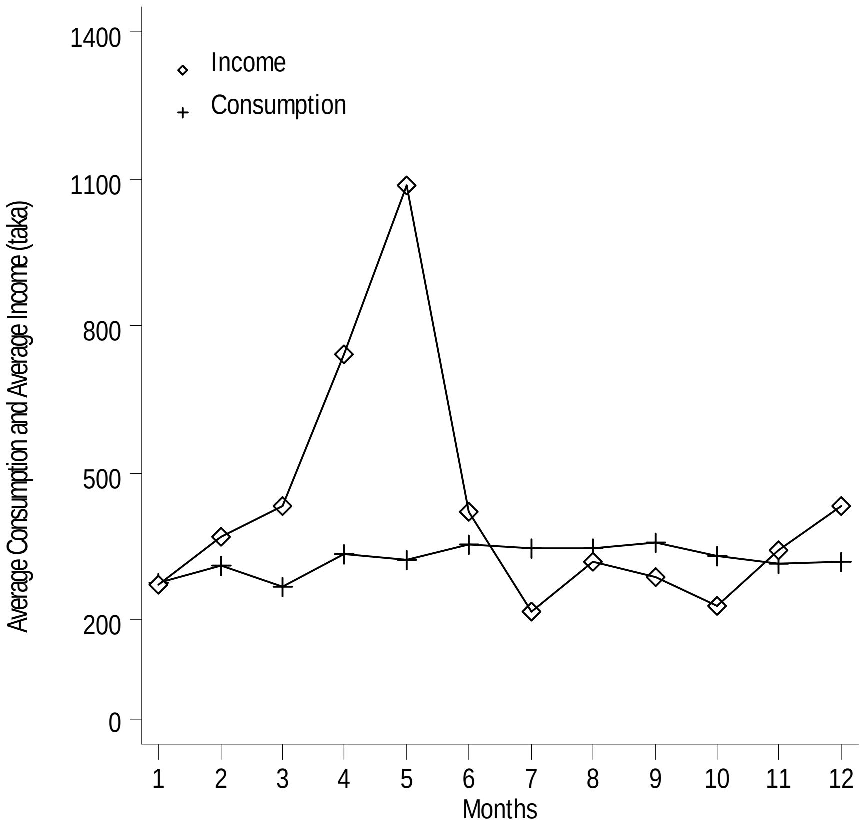


Figure 4b.
Fluctuations in Income and Consumption, Village B

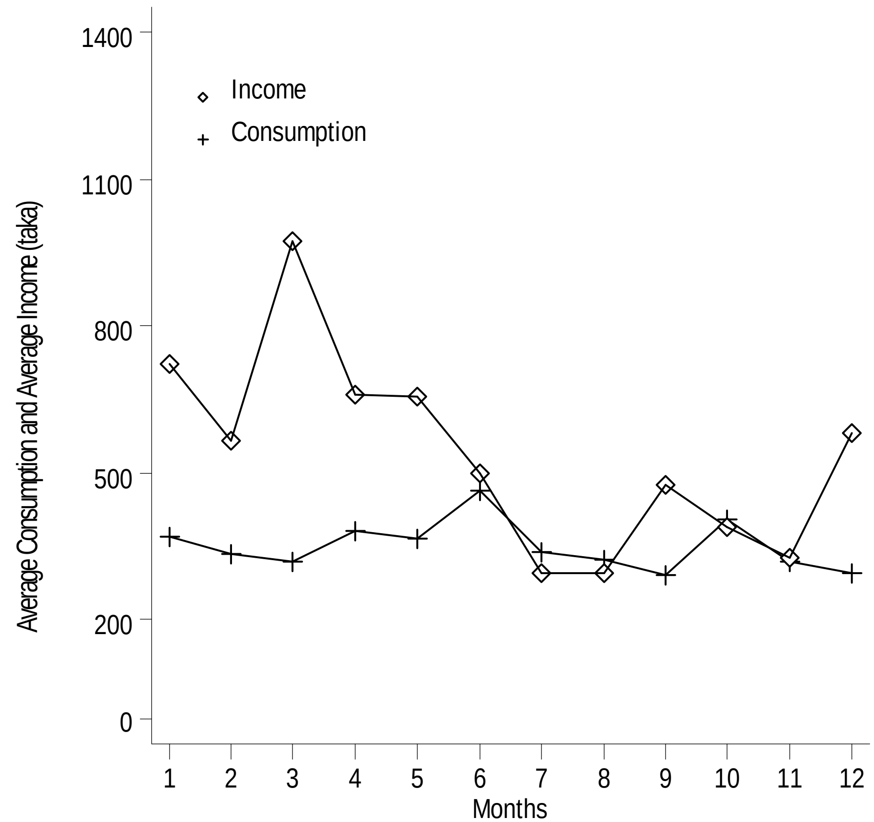


Figure 5a. Microcredit, Land and Consumption
Village A

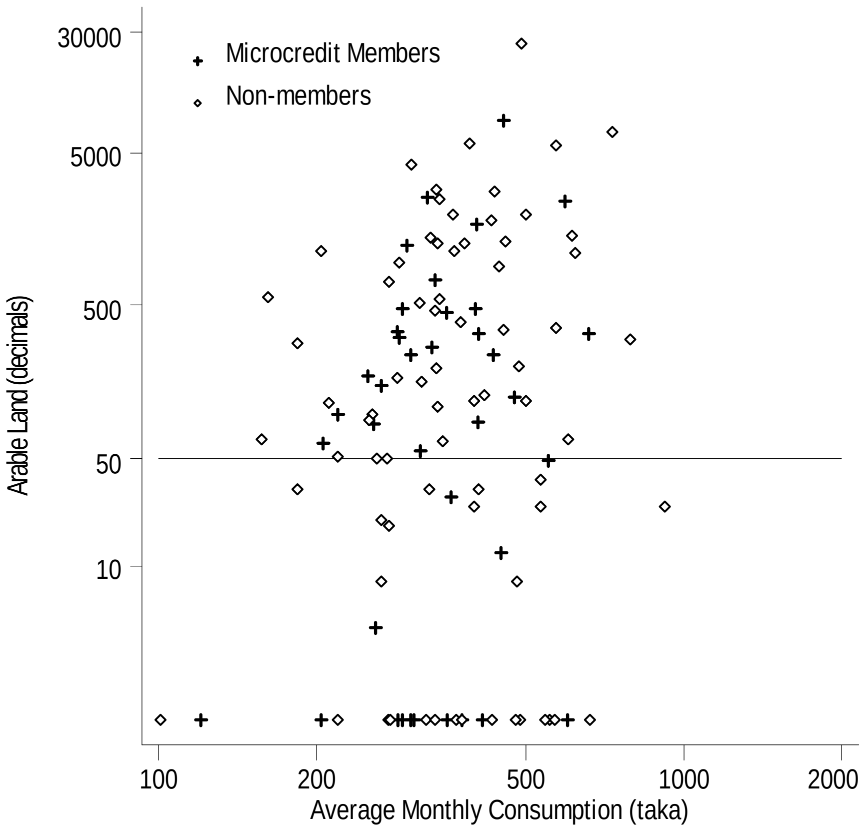


Figure 5b. Microcredit, Land and Consumption
Village B

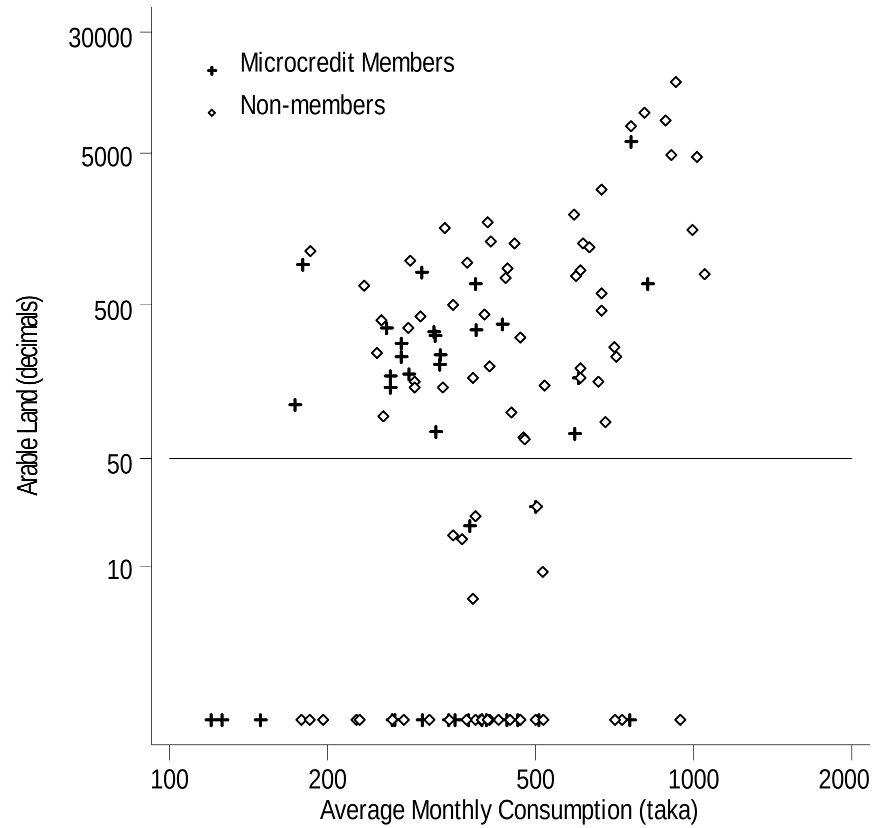


Figure 6a. Microcredit, Land and Income
Village A

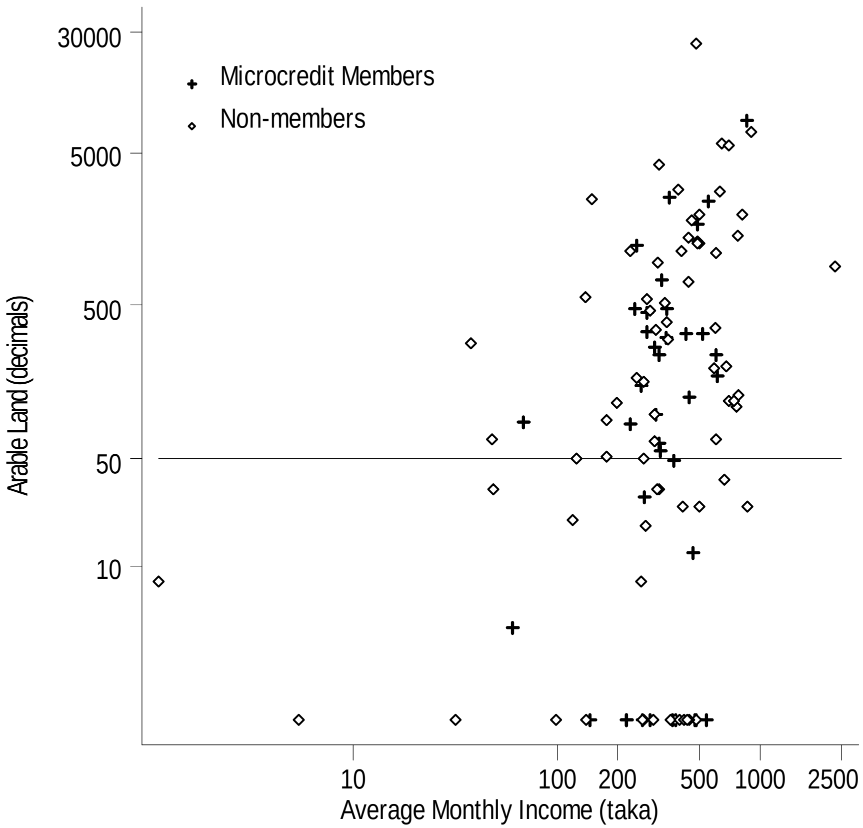
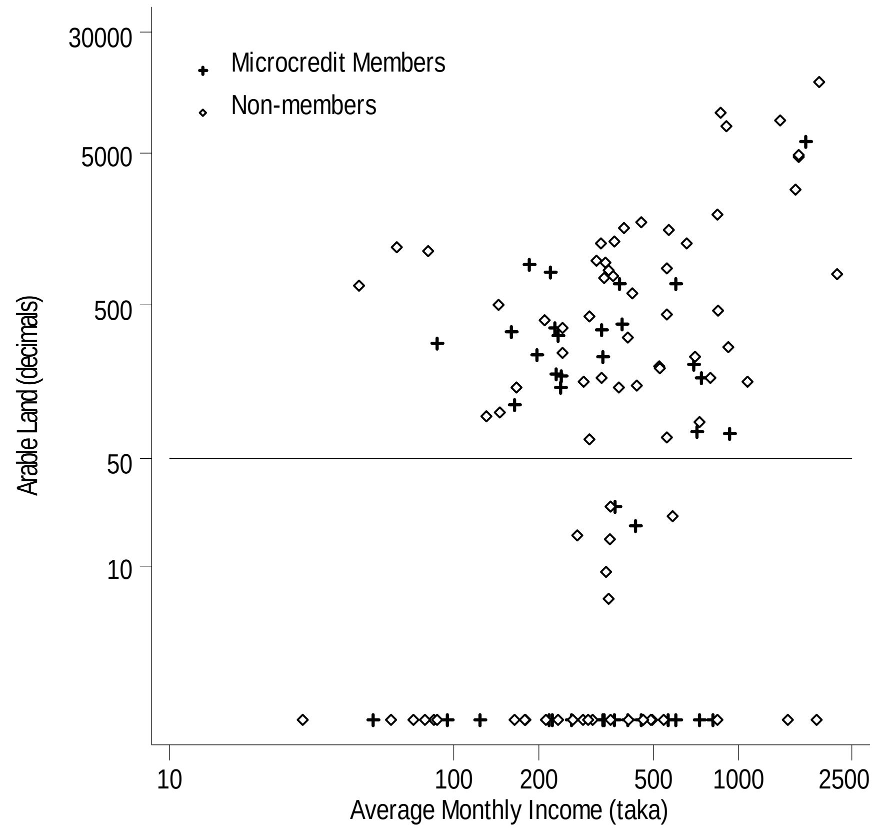


Figure 6b. Microcredit, Land and Income
Village B



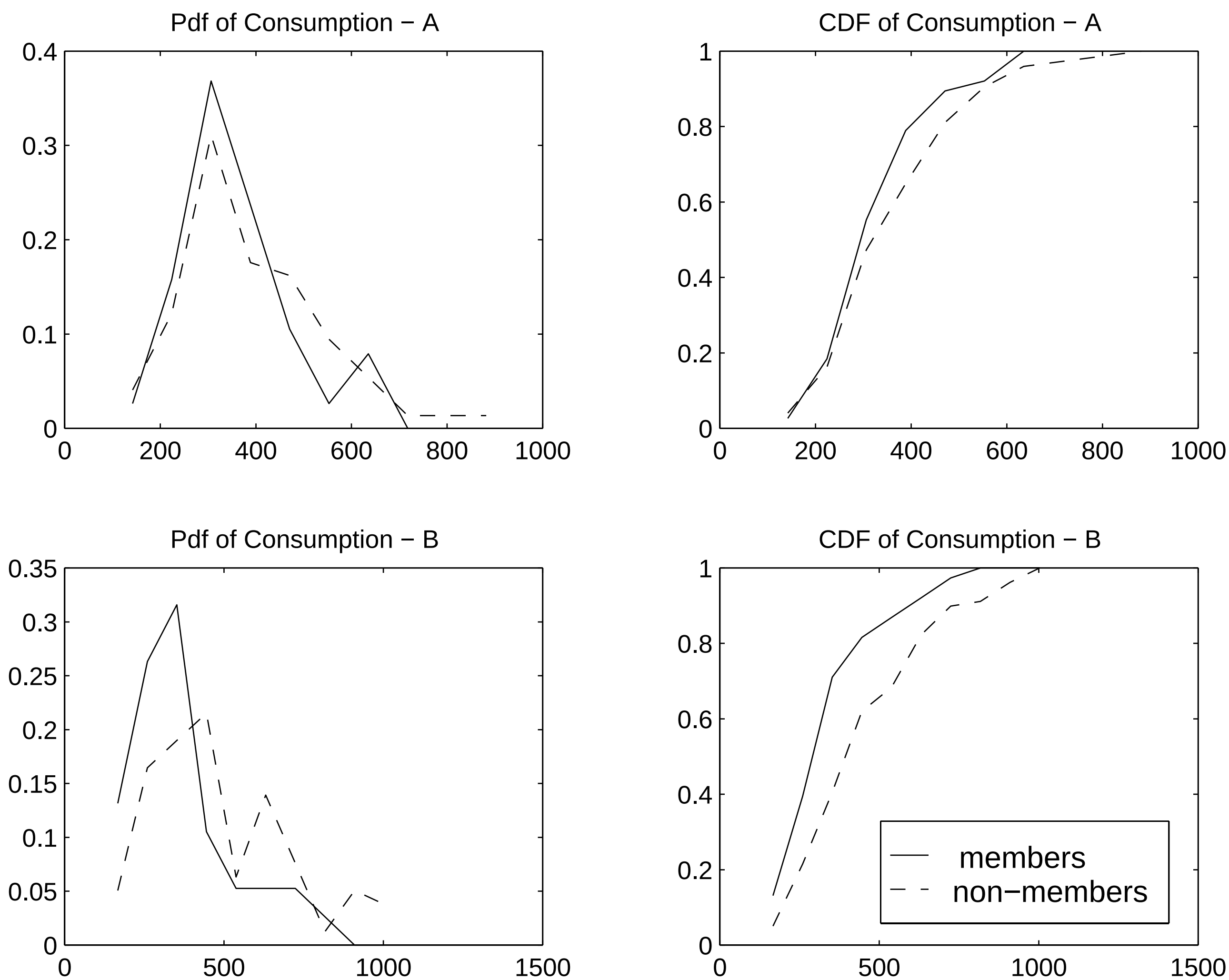


FIGURE 7A: All Consumption and Microcredit Membership

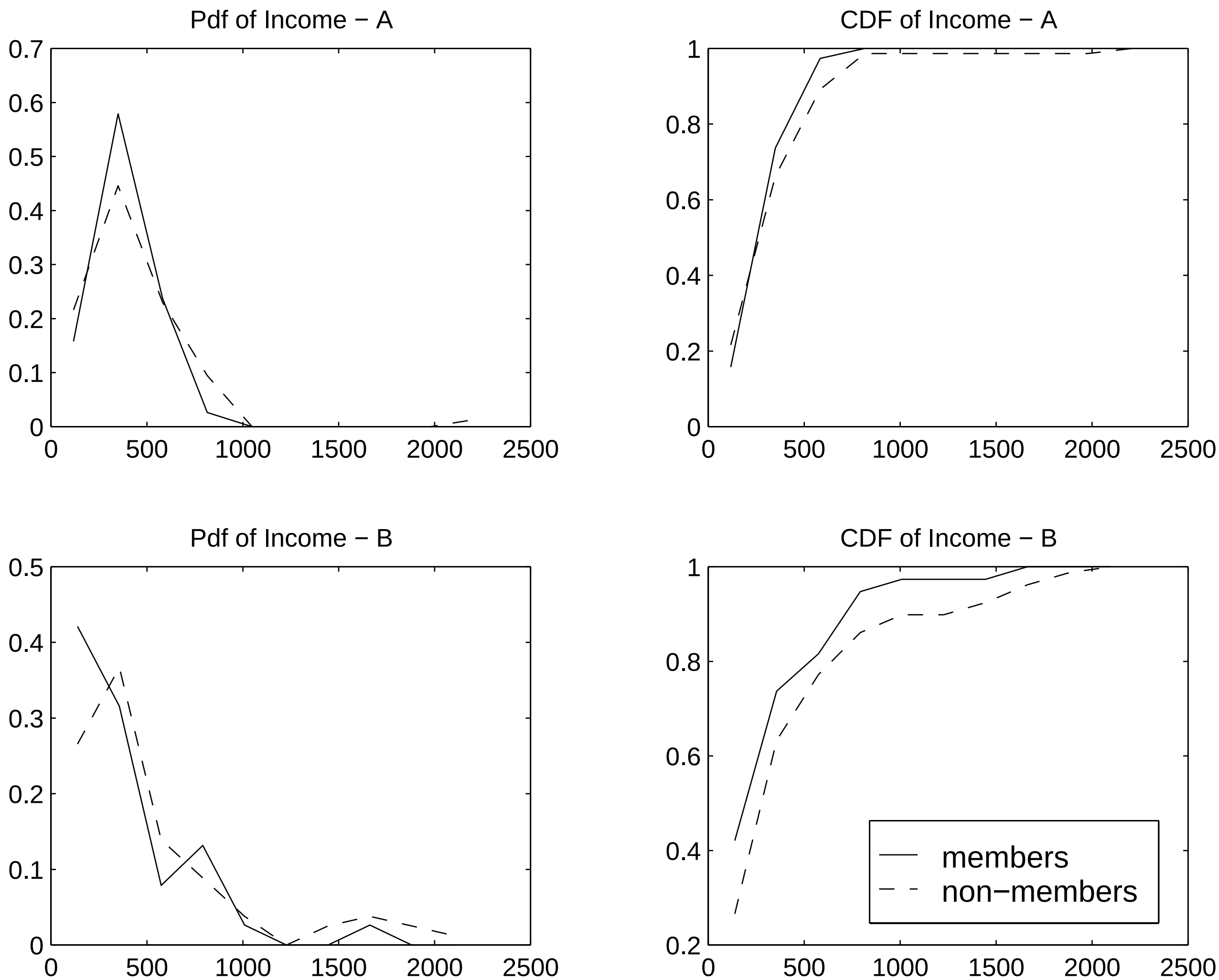


FIGURE 7B: All Income and Microcredit Membership

Figure 8a: CARA Utility
Vulnerability Coefficients with 95% Confidence Intervals, Village A

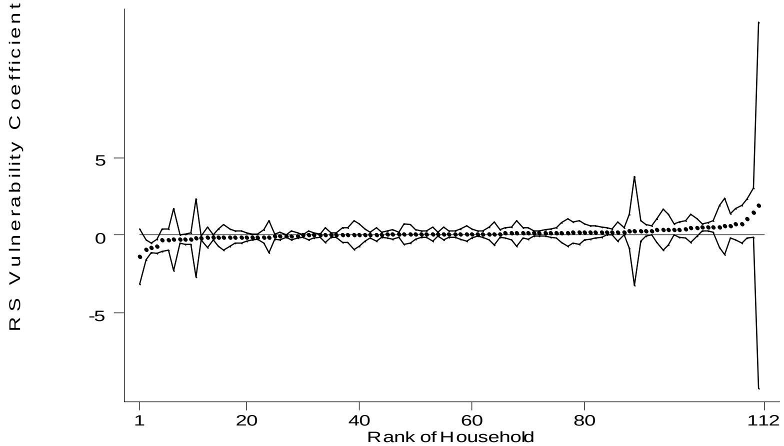


Figure 8b: CARA Utility
Vulnerability Coefficients with 95% Confidence Intervals, Village B

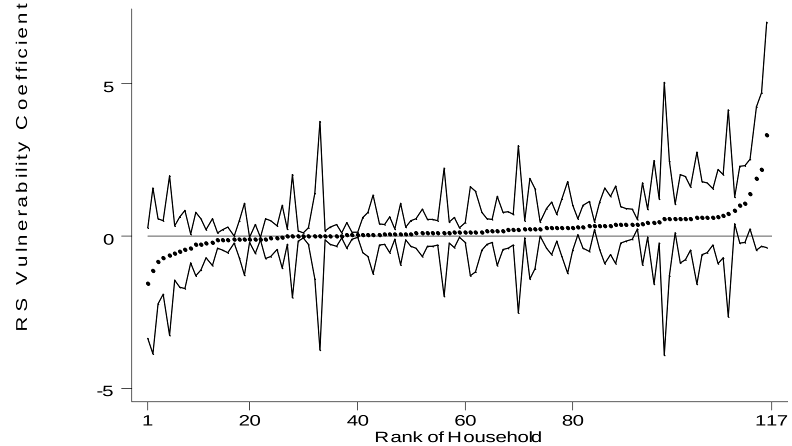


Figure 8c: CRRA Utility
Vulnerability Coefficients with 95% Confidence Intervals, Village A

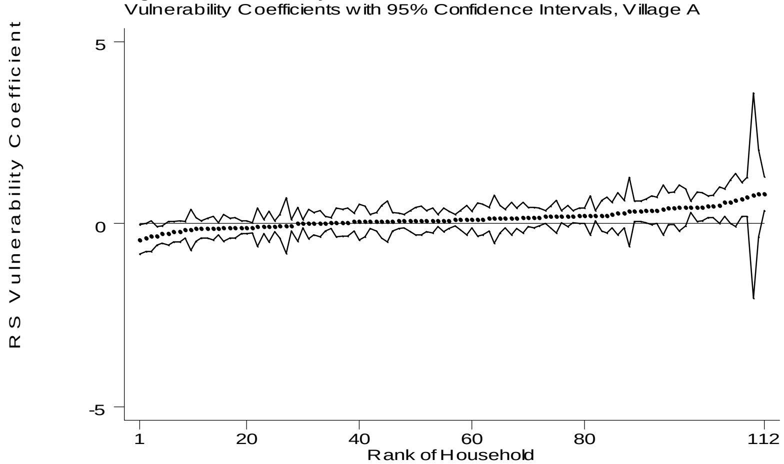
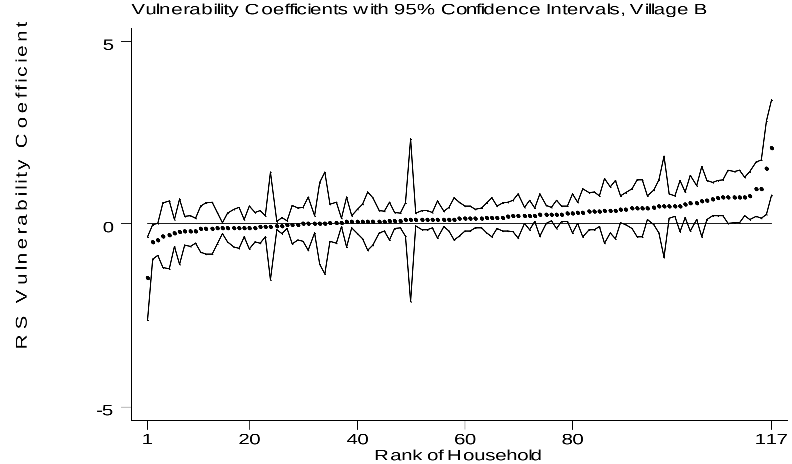


Figure 8d: CRRA Utility
Vulnerability Coefficients with 95% Confidence Intervals, Village B



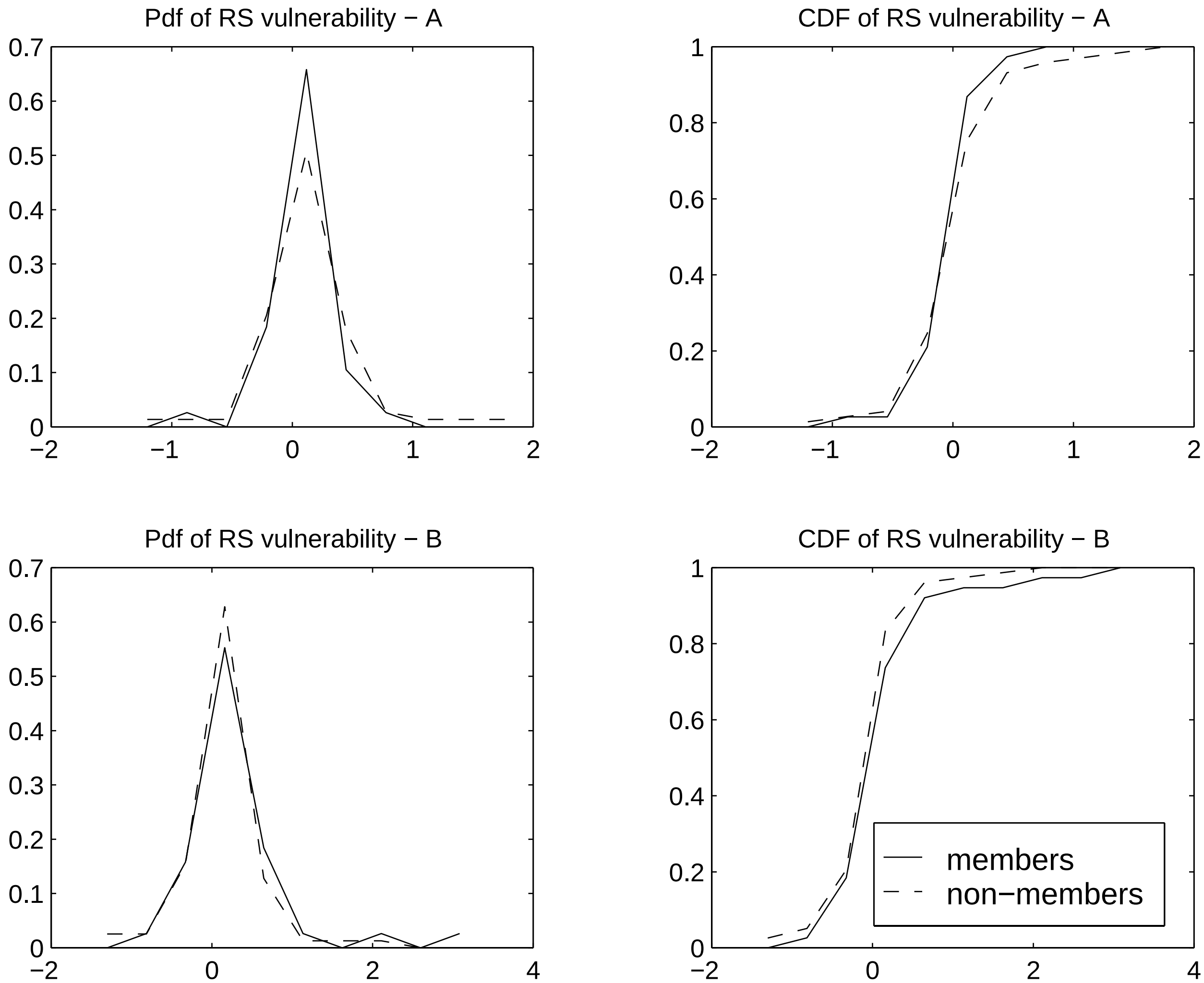


FIGURE 9A: RS Vulnerability (CARA) and Microcredit Membership

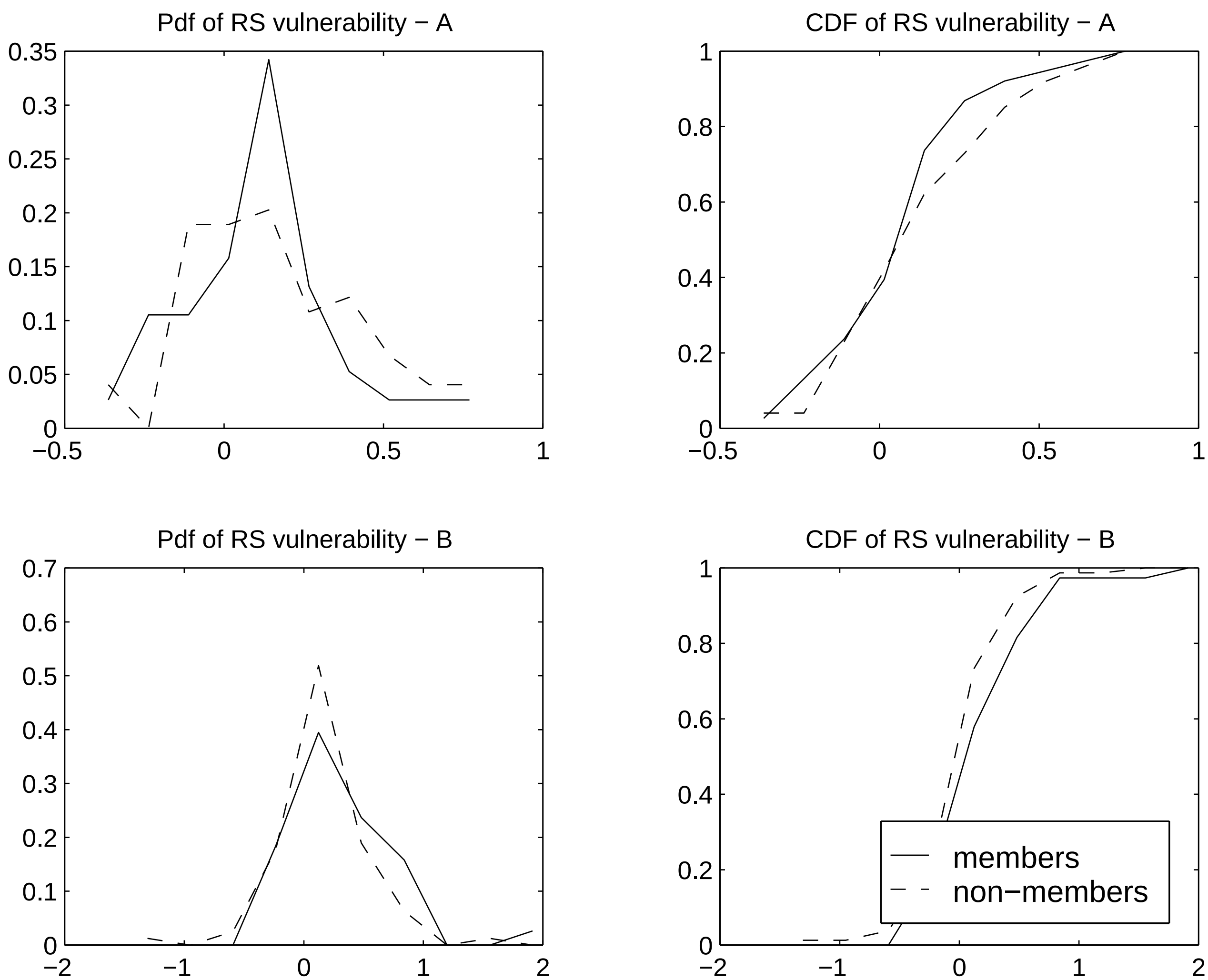


FIGURE 9B: RS Vulnerability (CRRA) and Microcredit Membership

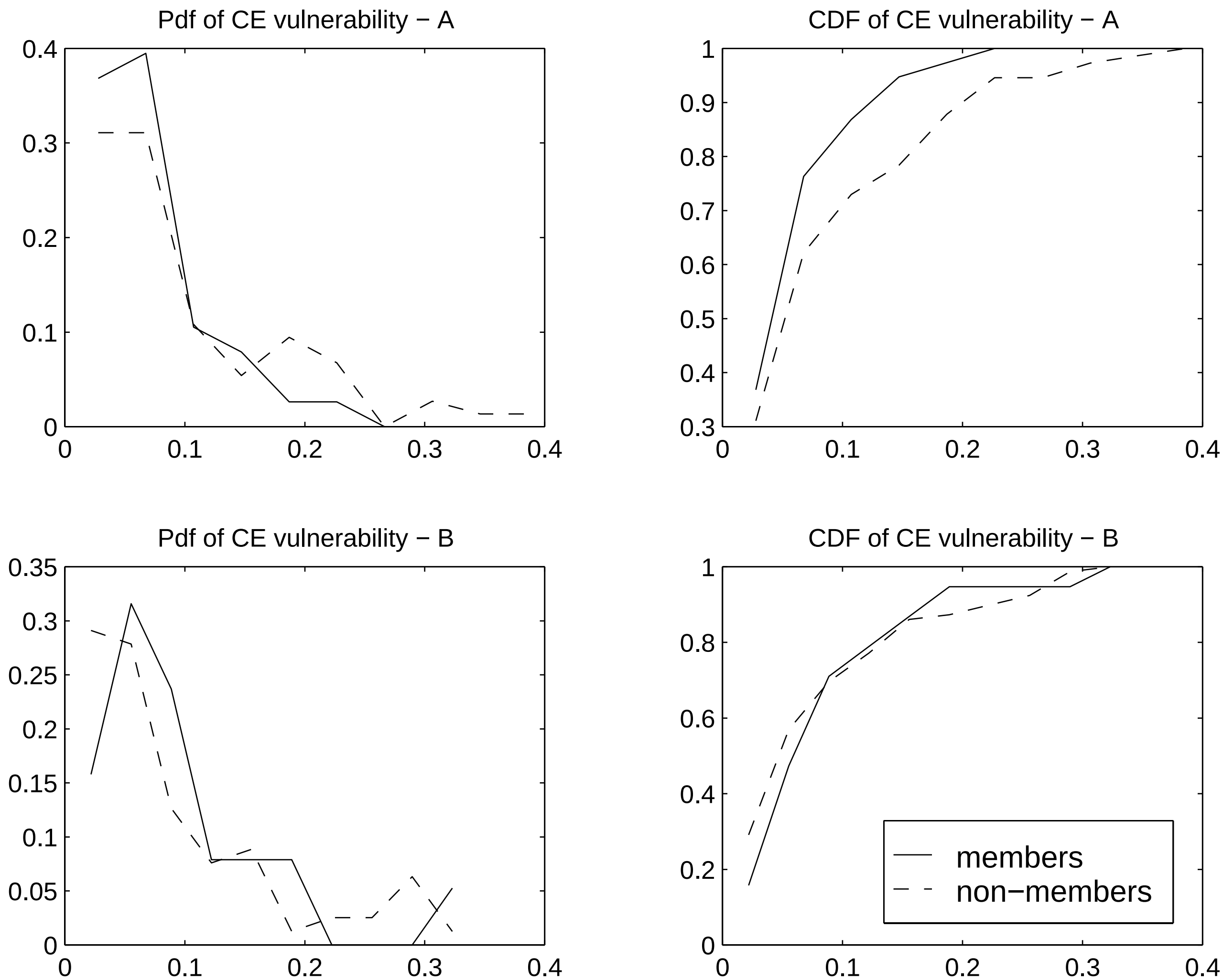


FIGURE 10A: CE Vulnerability (CARA) and Microcredit Membership

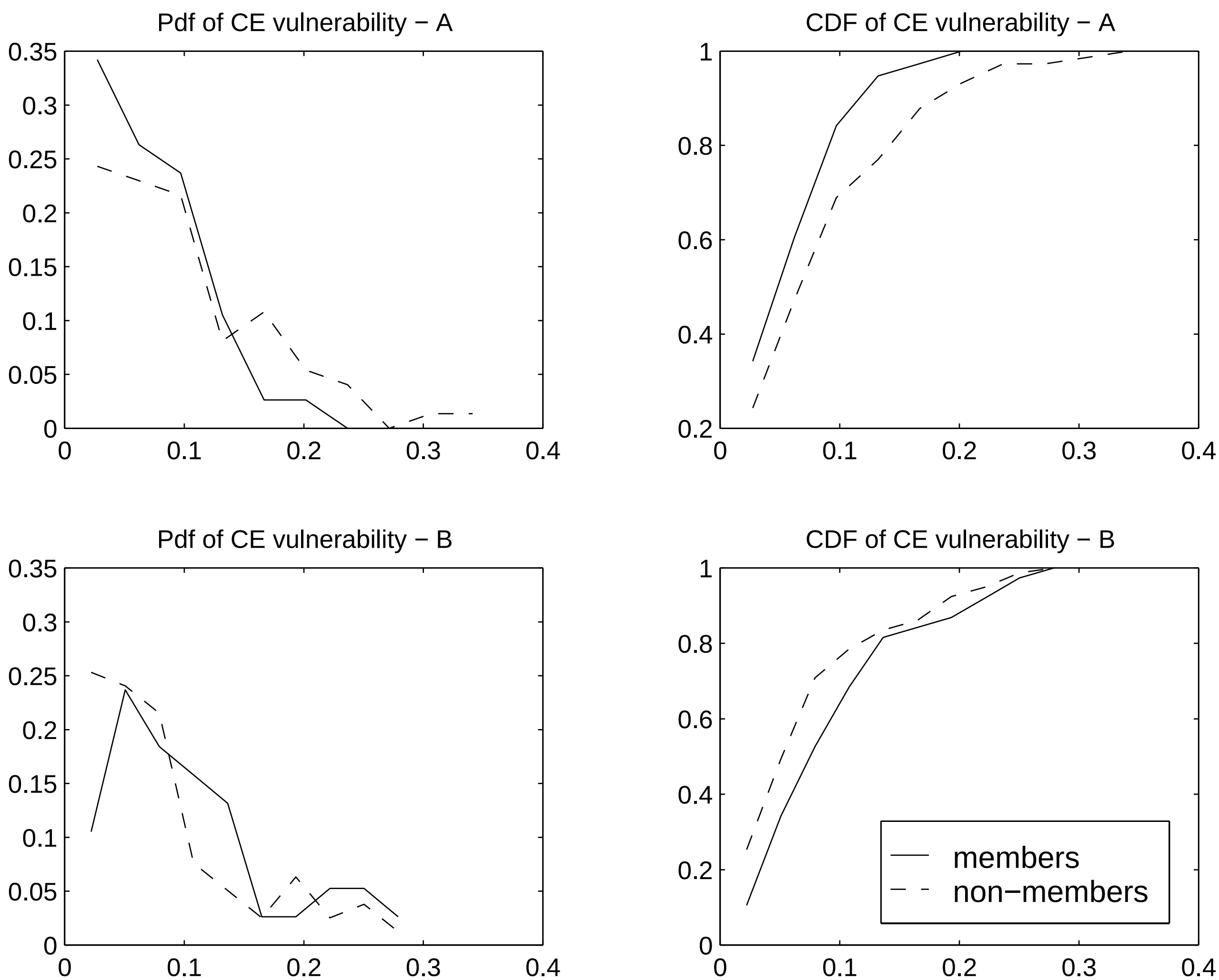


FIGURE 10B: CE Vulnerability (CRRA) and Microcredit Membership

Figure 11a.
CARA Vulnerability Coefficients, Village A

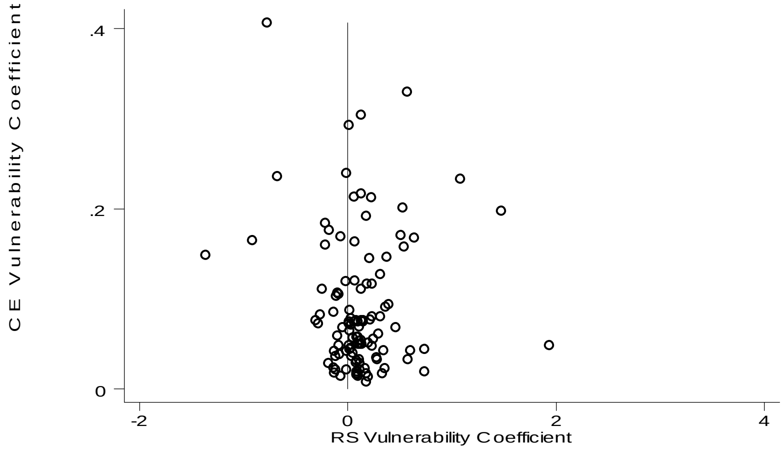


Figure 11b.
CARA Vulnerability Coefficients, Village B

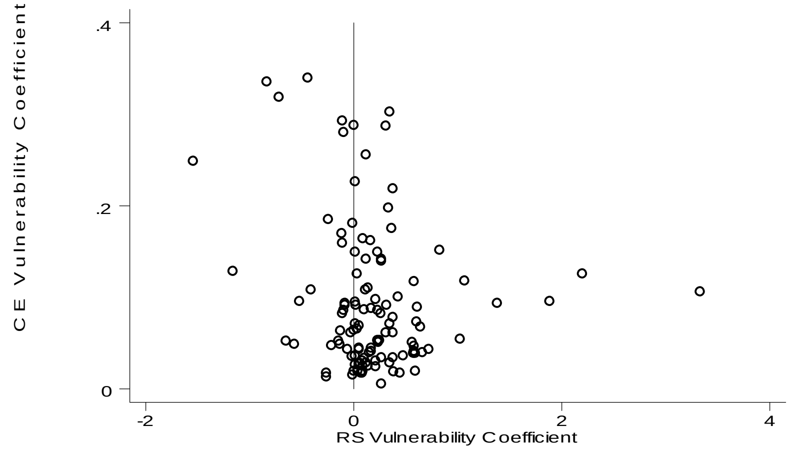


Figure 11c.
CRRA Vulnerability Coefficients, Village A

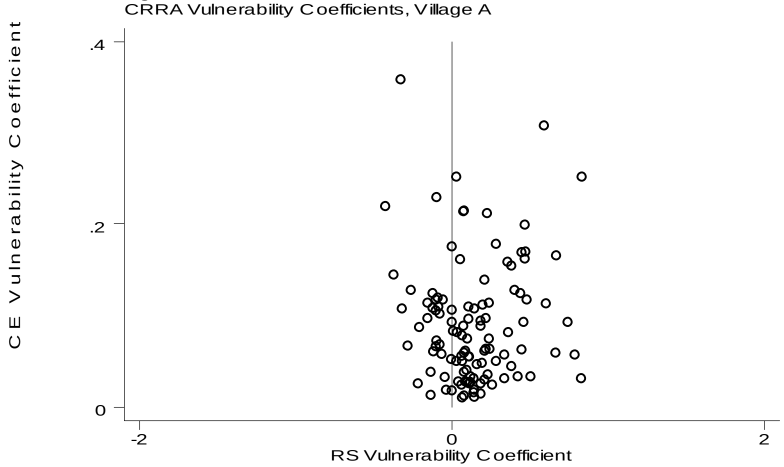


Figure 11d.
CRRA Vulnerability Coefficients, Village B