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The Effect of Nonagricultural Self-Employment Credit on Contractual Relations and Employment in Agriculture: The Case of Microcredit Programs in Bangladesh

by

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ABSTRACT

This paper examines the effect of group-based credit for the poor in Bangladesh, by gender of participant, on participating household's mix of agricultural contracts (quantities of land sharecropped and rented), and the supply of agricultural labor which takes the form of own-cultivation as opposed to agricultural wage labor. The group-based micro-credit programs examined provide production credit for nonagricultural activities to essentially landless and assetless rural households. Landless cultivators are more likely to have their contractual choices shaped by credit market constraints than others. On *a priori* grounds it is important to distinguish credit effects by the gender of participant. Male program credit, if properly monitored, should induce men to substitute away from supplying agricultural labor and contracting for agricultural land to supplying the nonagricultural labor required by the nonagricultural self-employment activity financed by the micro-credit program. Program participation by women, who are otherwise much less involved in income-generating activities, diversifies the sources of household income not merely by the type of activity undertaken but also across individuals within the household, outcomes that permit households to choose higher return but riskier agricultural contracts.

Econometric analysis of a 1991/92 household survey provides strong evidence that participation in these group-based micro-credit programs substantially alters the mix of agricultural contracts chosen by participating households. In particular, both female and male participation induce a significant increase in own-cultivation through sharecropping, coupled with a complementary increase in male hours in field crop self-employment and a reduction in male hours in the wage agricultural labor market, consistent with its presumed effects in diversifying income and smoothing consumption. Female credit effects are larger than male credit effects in increasing sharecropping and in reducing male wage labor and increasing agricultural self-employment, as predicted.

1. Introduction

This paper examines the effect of group-based credit for the poor in Bangladesh on the household's mix of agricultural contracts and the supply of agricultural labor. By "mix of agricultural contracts" we mean the quantities of land sharecropped and rented, and the extent to which agricultural labor supply takes the form of own-cultivation as opposed to agricultural wage labor. There seems to be a consensus that the risky nature of agriculture and the need to smooth consumption, coupled with absent or incomplete markets for insurance and credit, importantly determine the mix of agricultural activities that households undertake in rural South Asia. Cultivating agriculturalists require working capital to finance the inputs required for field crop cultivation, particularly as there is a substantial lag between the time that inputs are applied and the time that the final product is available for harvest and sale. Furthermore, in the absence of crop insurance, if the harvest fails, cultivators may require consumption credit to smooth consumption until the next harvest.

Landless cultivators are more likely to have their contractual choices shaped by credit market constraints than others. This effect will vary across households depending on their (heterogeneous) ability to smooth consumption *ex post* and their varying levels of risk aversion. If risk aversion declines with wealth, uninsured income risk may exacerbate income inequality. Lacking collateral, the landless may face higher costs of borrowing from landlords and other lenders if they seek to sharecrop or rent land. The inability to smooth consumption will likely result in alterations in tenant input choices. Rosenzweig and Binswanger (1993) find that limitations on *ex post* consumption-smoothing mechanisms are reflected in the agricultural investment portfolio of Indian farmers. They conclude that improvements in the abilities of farmers to smooth consumption would increase the overall profitability of agricultural investments. Similarly, among the landless, improvements in their ability to smooth consumption should increase the overall profitability of their mix of contractual choices. Lacking credit and insurance, many households may choose to limit their exposure to the uncertain agricultural environment and avoid tenancy contracts altogether. Even those who only sell labor in the agricultural market must smooth consumption between the peak and slack seasons when wages and rates of unemployment vary seasonally. For these wage workers, credit is often obtained from employers with an interlinked labor and credit contract.

Bangladesh has a marked seasonal pattern of agricultural production that results in large differences in the levels of income, consumption and the demand for labor across seasons. It is also subject to periodic agricultural failures due to flood and drought. Poor rural households are typically engaged primarily in agricultural pursuits --sharecropping and the sale of (male) labor in the agricultural labor market -- whose returns are subject to these weather shocks and weather induced seasonality.[1] The group-based micro-credit programs examined below provide production credit for nonagricultural activities to essentially assetless rural households. These household's can reduce their exposure to these weather-related uncertainties by diversifying into activities that respond less to weather shocks and seasonal weather patterns. These non-agricultural activities, by diversify income sources, may also lead households to choose riskier, but higher average return, agricultural contracts – choosing more to be cultivators than sellers of labor in the market.

This paper estimates the impact of participation in three group-based micro-finance programs (Grameen Bank, Bangladesh Rural Advancement Committee (BRAC), and Bangladesh Rural Development Board's (BRDB) Rural Development RD-12 program) , by gender of participant, on the mix of agricultural contracts, measured as male hours of wage labor, male hours of self-employment in agriculture, and the area of land sharecropped and rented in. We find strong evidence that participation in these group-based micro-credit programs substantially alters the mix of agricultural contracts chosen by participating households. In particular, there is a significant increase in own-cultivation through sharecropping coupled with a complementary increase in male hours in field crop self-employment and a reduction in male hours in the wage agricultural labor market. We find no strong effect of program credit on the fixed rental of land, a type of contractual relationship that is not common among the landless poor in Bangladesh. The results are consistent with the hypothesis that micro-credit financed nonagricultural self-

[1]We limit our definition of agricultural self-employment to field crop agriculture, excluding animal husbandry, tree crop cultivation, aquaculture and the like. Female field crop agricultural labor supply is relatively small even among the landless. This is illustrated with our survey data below.

employment projects induce households to choose higher risk agricultural contracts. The implication that higher risk contracts are associated with higher returns in consistent with the findings of Pitt and Khandker (1999) that micro-credit increases household consumption as well as smooths it across the seasons.

2. Microcredit, seasonality, and risk

In recent years, governmental and non-governmental organizations in many low income countries have introduced credit programs targeted to the poor. Many of these programs specifically target women based on the view that they are more likely to be credit constrained than men, have restricted access to the wage labor market, and have an inequitable share of power in household decision-making. The Grameen Bank of Bangladesh is perhaps the best-known example of these small-scale production credit programs for the poor, and over 90 percent of its clients are women.

All three of the Bangladesh programs examined below exclusively work with the rural poor. Although the sequence of delivery and the provision of inputs vary some from program to program, all three programs essentially offer production credit to the landless rural poor (defined as those who own less than half an acre of land) using peer monitoring as a substitute for collateral.[2] For example, the Grameen Bank provides credit to members who form self-selected groups of five. Loans are given to individual group members, but the whole group becomes ineligible for further loans if any member defaults. The groups meet weekly to make repayments on their loans as well as mandatory contributions to savings and insurance funds. Programs such as Grameen Bank, BRAC, and BRDB also provide non-credit services in areas such as consciousness-raising, skill development training, literacy, bank rules, investment strategies, health, schooling, civil responsibilities, and altering the attitude of and toward women.[3]

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[2]Theoretical aspects of targeted group-based lending to the poor are well summarized in Rashid and Townsend (1993). Some non-production lending does take place. In the Grameen Bank, for example, a group fund, financed by the weekly contributions of group members, is used to make consumption loans to group members. More recently, Grameen has offered housing loans to group members as well.

[3] As part of Grameen Bank's social development program, all members are required to memorize, chant, and follow the "Sixteen Decisions". These decisions include "We shall keep our families small", "We shall not take any

The majority of borrowers from the micro-credit programs studied in this paper use their loans to finance nonfarm activities and, during the time period covered by our data, lending by micro-credit programs to finance field crop agriculture was prohibited. If smoothing consumption is an important motivation for poor rural households, they are likely to choose self-employment activities that generate income streams that do not highly covary seasonally with income from agricultural pursuits. Access to monitored production credit, such as that provided by group-based micro-credit programs, can also help households free up other sources of financing than can be used as working capital or to smooth consumption directly.

The three group-based credit programs (Grameen Bank, Bangladesh Rural Advancement Committee (BRAC), and Bangladesh Rural Development Board's (BRDB) Rural Development RD-12 program) examined are the major micro-credit programs in Bangladesh. Participation in these schemes requires that the area of cultivable land owned not exceed one-half acre and that ownership of other assets be of comparable magnitude. Monitored production credit is unlikely to be a perfect substitute for access to working capital or consumption credit. Peer monitoring in these group-based schemes is sufficiently close that households may have to carry out the funded project using the borrowed funds and the participant's time input as described in the application to borrow, even if both time and funds would be allocated differently in the absence of monitoring. However, even perfect monitoring does not necessarily mean that monitored production credit can not substitute somewhat for consumption credit or for prohibited agricultural credit. If a household wishes to devote resources obtained from savings, inter-household transfers, or borrowing from money-lenders or other source to a production activity in the absence of group-based credit, it may, in the presence of group-based lending programs, substitute group-based credit for those resources, thus freeing up those funds for other uses. In this way, simply by relaxing the household's constraints on borrowing and transfers, monitored production credit may help households alter the mix of all other income-generating activities, including the mix agricultural contracts, as well as smooth consumption. Access to group-based micro-credit may enhance the household's ability to borrow from other sources or obtain

dowry in our sons' wedding, neither shall we give any dowry in our daughters' wedding", "We shall not practice child marriage", and "We shall educate our children".

transfers, which may make it more likely to undertake the own-cultivation of field crops, increase self-employment in field crop agriculture and reduce labor supply to the agricultural labor market.

In an earlier paper using the same data as here, Pitt and Khandker (1998) find that participation in these credit programs, as measured by quantity of borrowing, is a significant determinant of a number of important household and individual outcomes including women's and men's labor supply and household consumption. They also rejected the hypothesis that program credit is exogenous in the determination of many of these outcomes. That is, unobserved variables that affect credit program participation (as measured by borrowing) also affect these outcomes, such as consumption and men's labor supply, conditional on credit program participation. In that paper, seasonality in behavior is treated by including seasonal dummy variables in the conditional demand equations.

In subsequent work, Pitt and Khandker (1999) allow for the effects of program credit to vary by season by including season-credit interactions. If smoothing consumption across seasons is an important motivation for participating in these credit programs, households with more seasonal fluctuations in consumption and labor supply than average would be more likely to participate. This suggests that the correlation between the unobserved determinants of program credit and consumption and labor supply may vary in intensity seasonally. In particular, Pitt and Khandker (1998) found that there was a significant and negative correlation between program credit residuals and per capita consumption residuals implying that consumption-poor households (conditional on all the included regressors) were more likely to participate in group-based credit programs. If seasonal consumption smoothing were a motivation for credit program participation, one should expect that the correlation between low season consumption and credit would be bigger in absolute value (that is, more negative algebraically) than the correlation between high season consumption and credit. The results reported in Pitt and Khandker (1999) find exactly this pattern. They find that the only self-selection into these credit programs with respect to consumption expenditure arises from heterogeneity in "hungry season" (*Aus*) consumption expenditure. That is, it is the extent of lean season poverty that selects household into these programs. Thus, the need to smooth consumption seems to be an important determinant of program participation. Moreover, Pitt and Khandker (1999) demonstrate that participation is indeed quite effective at smoothing both household consumption and the labor supply of males across the seasons.

This enhanced ability to smooth consumption arising from microcredit should permit households to choose riskier but higher yielding contracts from among those offered in agricultural markets. It is this hypothesis that this paper examines empirically. Furthermore, the earlier study (Pitt and Khandker, 1998) found that credit provided to women was more likely to influence consumption and labor supply differently than credit provided to men. Thus, it is important to distinguish credit effects by the gender of participant. One might believe *a priori* that woman's credit has a different impact on the mix of agricultural contracts and on male agricultural labor supply than does male credit. Male program credit, if properly monitored, should cause men to substitute away from supplying agricultural labor and contracting for agricultural land to supplying the nonagricultural labor required by the nonagricultural self-employment activity financed by the micro-credit program. Furthermore, since women are otherwise much less involved in income-generating activities, women's program participation diversifies the sources of household income not merely by the type of activity undertaken but diversifies it across individuals within the household. The effect of health and other person-specific shocks on the smoothness of consumption is lessened when a household diversifies income generation across it's members.

3. Estimation Methods

A. Identification from a Quasi-experiment

The econometric methods used in the analysis is essentially the same as that presented in Pitt and Khandker (1998) and hence only an abbreviated version of it here. This paper estimates the conditional demands for a set of household behaviors, conditioned on the household's program participation as measured by the quantity of credit borrowed.[4] Leaving seasonal

[4]The quantity of credit is, of course, only one measure of the flow of services associated with participation in any one of the group-based lending programs. These programs are more than just lending institutions. Nevertheless, the quantity of credit is the most obvious and well measured of the services provided.

considerations aside for the moment, consider the reduced form equation (1) for the level of participation in one of the credit programs (C_{ij}), where level of participation will be taken to be the value of program credit that household i in village j borrows,

$$C_{ij} = X_{ij}\beta_c + Z_{ij}\pi + \mu_j^c + \epsilon_{ij}^c \qquad \textbf{(1)}$$

where X_{ij} is a vector of household characteristics (e.g. age and education of household head), Z_{ij} is a set of household or village characteristics distinct from the X's in that they affect C_{ij} but not other household behaviors conditional on C_{ij} (see below), β_c, and π are unknown parameters, μ_j^c is an unmeasured determinant of C_{ij} that is fixed within a village, and ϵ_{ij}^c is a nonsystematic error that reflects unmeasured determinants that vary over households.

The conditional demand for outcome y_{ij} (such as agricultural wage labor supply or area of land under sharecrop) conditional on the level of program participation C_{ij} is

$$y_{ij} = X_{ij}\beta_y + C_{ij}\delta + \mu_j^y + \epsilon_{ij}^y \qquad \textbf{(2)}$$

where β_y and δ are unknown parameters, μ_j^y is an unmeasured determinant of y_{ij} that is fixed within a village, and ϵ_{ij}^y is a nonsystematic error reflecting, in part, unmeasured determinants of y_{ij} that vary over households. The estimation issue arises as a result of the possible correlation of μ_j^c with μ_j^y, and of ϵ_{ij}^c with ϵ_{ij}^y. Econometric estimation that does not take these correlations into account may yield biased estimates of the parameters of equation (2) due to the endogeneity of credit program participation C_{ij}.

The standard approach to the problem of estimating equations with endogenous regressors, such as equation (2), is to use instrumental variables. In the model set out above, the exogenous regressors Z_{ij} in equation (1) are the identifying instruments. Unfortunately, it is difficult to find any regressors Z_{ij} that can justifiably be used as identifying instrumental variables. Lacking identifying instruments Z_{ij}, the sample survey was constructed so as to provide identification through a quasi-experimental design.

Our sample of households includes households in villages that do not have access to a group-based credit program. If credit program placement across the villages of Bangladesh is attentive to the village effects :$_j$, identifying program effects by comparing households in nonprogram villages with households in program villages without controlling for the selectivity of program placement will generally result in biased estimates of program effects. Using a village fixed effects estimation technique may remove the source of correlation between program placement and the behavior of interest, however, without further exogenous variation in program availability, the credit effect is not identifiable from a sample of self-selected households as it is captured within the village fixed effects.[5] The parameter of interest, *, the effect of participation in a credit program on the outcome y_{ij}, can be identified if the sample also includes households in villages with treatment choice (*program villages*) who are excluded from making a treatment choice by exogenous rule. That exogenous rule is the restriction that households owning more than 0.5 acres of <u>cultivable</u> land are precluded from joining any of the three credit programs.[6]

There are a number of households in our sample that are program participants yet had more than 0.5 acres of land at the time of program entry, raising the possibility of mistargeting and potential bias in econometric results relying on this targeting rule. It appears that some of this excess land is either uncultivable or marginally so. Pitt (1999) demonstrates that the value per acre of land owned by program participating households who also own more than 0.5 acres of cultivable land at the time of joining is a small proportion of the value per acre of the cultivable land of program participants owning less than 0.5 acres of cultivable land at the time of joining. This suggests that program officers are using some notion of "effective" units of cultivable land in determining eligibility rather than of the type of mistargeting that would result in econometric bias. Pitt (1999) discusses this issue at length and demonstrates that treating the exogenous targeting rule to be greater than 0.5 acres provides a consistent estimator for certain types of mistargeting. He finds that application of targeting rules greater than 0.5 acres (up to 2.0 acres) actually slightly strengthens the qualitative results on the effect of credit by gender on household consumption. In order to ascertain the sensitivity of results to possible mistargeting, each of the

[5]In addition, the effect of any observed village characteristics that are thought to influence y_{ij}, such as prices and community infrastructure, are not identifiable.

[6] The validity of the assumption that landownership is exogenous is defended at length in Pitt and Khandker (1998).

models will be estimated with both the *de jure* 0.5 acre rule and a 1.0 acre treatment choice rule.

To illustrate the identification strategy, consider a sample drawn from two villages -- village 1 does not have the program and village 2 does; and, two types of households, landed (X_{ij}=1) and landless (X_{ij}=0). Innocuously, we assume that landed status is the only observed household-specific determinant of some behavior y_{ij} in addition to any treatment effect from the program. The conditional demand equation is:

$$y_{ij} = C_{ij}\delta + X_{ij}\beta_y + \mu_j^y + \epsilon_{ij}^y \tag{3}$$

The exogeneity of land ownership is the assumption that $E(X_{ij}, \epsilon_{ij}^y) = 0$, that is, that land ownership is uncorrelated with the unobserved household-specific effect. The expected value of y_{ij} for each household type in each village is:

$$E(y_{ij} \mid j=1, X_{ij}=0) = \mu_1^y \tag{4a}$$

$$E(y_{ij} \mid j=1, X_{ij}=1) = \beta_y + \mu_1^y \tag{4b}$$

$$E(y_{ij} \mid j=2, X_{ij}=1) = \beta_y + \mu_2^y \tag{4c}$$

$$E(y_{ij} \mid j=2, X_{ij}=0) = p\delta + \mu_2^y \tag{4d}$$

where p is the proportion of landless households in village 2 who choose to participate in the program. It is clear that all the parameters, including the effect of the credit program δ, is identified from this design. In particular, the estimator of the program effect δ is a variant of the differences-in-the-differences estimator widely applied in the general program evaluation literature. To see this, note that an estimate of δ is obtained from the following difference-in-the-difference:[7]

$$[E(y_{ij} \mid j=2, X_{ij}=0) - E(y_{ij} \mid j=2, X_{ij}=1)] - [E(y_{ij} \mid j=1, X_{ij}=0) - E(y_{ij} \mid j=1, X_{ij}=1)] \tag{4e}$$

[7]However, as Pitt (1999) points out, since this is a quasi-experiment, not an actual experiment, the direct application of (4e) would most likely result in a downward biased estimate of δ. The regression approach applied here is quite necessary to control for differences in other observed and unobserved variables across the four groups identified in equations (4a) though (4d).

To illustrate the log-likelihood maximized, consider the case of a binary treatment (I_c=1 if treatment chosen, 0 otherwise) and a binary outcome (I_y=1 if outcome is true, 0 otherwise). This is the most difficult model to identify in that nonlinearity arising from the choice of an error distribution is insufficient to identify the credit effect parameter δ. Distinguishing between households not having choice because they reside in a non-program village and households residing in a program village that do not have choice because of the application of an exogenous rule (landowning status), and suppressing the household and village subscripts i and j, the likelihood can be written as:

$$
\begin{aligned}
\log L(\beta,\delta,\mu,\rho) = & \sum_{choice} \log \Phi_2((\mu_p^c + X\beta_c)d_c, (\mu_p^y + X\beta_y + \delta I_c)d_y, \rho d_c d_y) \\
& + \sum_{\substack{no\ choice \\ program\ village}} \log \Phi((\mu_p^y + X\beta_y)d_y) + \sum_{nonprogram\ village} \log \Phi((\mu_n^y + X\beta_y)d_y)
\end{aligned}
\tag{5}
$$

where Φ_2 is the bivariate standard normal distribution, Φ is the univariate standard normal distribution, μ_p^c are the village-specific effects influencing participation in the credit program in program villages, μ_p^y are village-specific effects influencing the binary outcome I_y in program villages, μ_n^y are the corresponding village-specific effects in nonprogram villages, and $d_c = 2*I_c - 1$ and $d_y = 2*I_y - 1$.[8] The errors ϵ_{ij}^c and ϵ_{ij}^y are normalized to have unit variance and correlation coefficient ρ. Village-specific effects (μ_n^c) influencing the demand for program credit are not identifiable for villages that do not have programs.

The first part of the likelihood is the joint probability of program participation and the binary outcome I_y conditional on participation for those households that are <u>both</u> eligible to join the program (*choice*) and reside in a village with the program (*program village*). This part of the likelihood corresponds to the expectation (4d). Without regressors (Z) that influence the probability of program participation but not the outcome I_y conditional on participation, the parameter δ, the effect of credit on the outcome y, is not separately identified from the parameters μ_p^y and β_y from this part of the likelihood. The second part of the likelihood is the

[8]Implicit in this setup is the assumption that the effect of the treatment (δ) is the same for all individuals, an assumption which is common in the program evaluation literature (Moffitt 1991).

(univariate) probability of binary outcome I_y for landed households in program villages and corresponds to expectation (4c). These households are precluded from joining the program by their landed status. The last part of the likelihood is the probability of the outcome I_y for all households, landed and landless, in villages without a program and corresponds to expectations (4a and 4b). If one of the regressors in X is a binary indicator of landed status, this part of the likelihood is required for identification. If landed status is a continuous measure of landholding, then the model is identified without the last part of the likelihood. In this case, the parameter $\$_y$ in (3) is identified from variation in landholding within the program villages (j=2) and a sample of nonprogram villages is not required.

Even if land ownership is exogenous for the purposes of this analysis, it is necessary that the "landless" and the "landed" can be pooled in the estimation. In order to enhance the validity of this assumption, we restrict the set of nontarget households used in the estimation to those with less than 5 acres of owned land. In addition, we include the quantity of land owned as one of the regressors in the vector X_{ij} and include a dummy variable indicating the target/nontarget status of the household.

The exclusion restrictions that identify the effects of credit on the outcomes y_{ij} are the interactions of a dummy variable indicating if the household has the choice to join the credit program (which requires meeting the land ownership rule and residing in a village with a credit program) and all the exogenous variables of the model, X_{ij} and $:_j$. Consequently, the model is not nonparametrically identified. That is, if the linear indices $X_c($ and $(X_y\$+*I_c)$ in (5) were replaced by nonparametric functions of the X's, and I_c the model is not identified.

B. Identification of the Impact of Gender-Specific Credit using Single-Sex Groups

An important question of this research is whether behavior is affected differently by credit if the program participant is a woman or a man. For that reason, the reduced form credit equation is disaggregated by gender

$$C_{ijf} = X_{ij}\beta_{cf} + \mu^{c}_{jf} + \epsilon^{c}_{ijf} \qquad \textbf{(6)}$$

$$C_{ijm} = X_{ij}\beta_{cm} + \mu^{c}_{jm} + \epsilon^{c}_{ijm} \qquad \textbf{(7)}$$

where the additional subscripts f and m refer to females and males respectively. The conditional household outcome equations allow for seasonal intercept dummy variables as well as separate female and male credit effects by season:

$$y_{ijs} = X_{ijs}\beta_{y} + \mu^{y}_{j} + \alpha_{s} + \sum_{s} C_{ijf}D_{jfs}\delta_{fs} + \sum_{s} C_{ijm}D_{jms}\delta_{ms} + \epsilon^{y}_{ijs} \qquad \textbf{(8)}$$

where D_{jfs} and D_{jms} are village specific indicator variables such that D_{jfs} takes the value of one in village j in season s if there is a female group in village j, and zero otherwise.

Additional identification restrictions are required when there are both male and female credit programs with possibly different effects on behavior. Identification of gender-specific credit is achieved by making use of another quasi-experimental attribute of these programs and the survey. All program groups are single-sex and not all villages have both a male and a female group. The sample includes some households from villages with only female credit groups, so that males in landless households are denied the choice of joining a credit program, and some households from villages with only male credit groups, so that landless females are denied program choice.[9] In particular, of the 87 villages in the sample, 15 had no credit program, 40 had credit-groups for both females and males, 22 had female-only groups and 10 had male-only groups. The necessary assumption is that the availability of a credit group by gender in a village is uncorrelated with the household errors $,^{y}_{ij}$, conditional on X_{ij} and the village fixed effects $:_{j}$. As each village had only one type of credit program available, and it is assumed that the type of credit program (BRDB, BRAC or Grameen) is uncorrelated with the household errors $,^{y}_{ij}$, conditional on X_{ij} and the village fixed effects $:_{j}$, there is no need to model which of the

[9]Although rules prohibit more that one adult member of each household to belong to a credit group, in our data there were a number of households in which both a male and female adult belonged. As a consequence, we do not restrict the probability of having both a male and female group member to be zero in the estimation.

programs members of a household join.[10]

While the likelihood given by (5) illustrates the general principal and method used, the actual likelihoods maximized have been altered to allow for other aspects of our data. Male and female credit, and the most of the dependent variables (male hours of wage labor, male hours of self-employment in field crop agriculture, and the area of land sharecropped and rented in) are limited dependent variables with a mass point at zero. Consequently, the likelihoods contain trivariate normal distribution functions because two credit equations (6) and (7) are being estimated simultaneously with a limited dependent variable outcome equation. In addition, the sample design is choice-based (see Section 4 below). In particular, program participants are purposely over-sampled. The Weighted Exogenous Sampling Maximum Likelihood (WESML) methods of Manski and Lerman (1977) were grafted onto the limited information maximum likelihood (LIML) methods described above in the estimation of both parameters and the parameter covariance matrix.[11] WESML estimates are obtained by maximizing a weighted log likelihood function with weights for each choice equal to the ratio of the population proportion to the sample proportion for that choice. To remind the reader of these crucial aspects of the maximum likelihood approach taken in this paper, the method is referred to as WESML-LIML-FE, which stands for Weighted Exogenous Sampling Maximum Likelihood - Limited Information Maximum Likelihood - (Village) Fixed Effects. Pitt and Khandker (1998) provides an explicit characterization of the likelihood actually maximized as well as the asymptotic covariance matrix.

The specifications of the conditional demand demand and supply equations presented here differ from those in Pitt and Khandker(1998) in that credit effects are allowed to vary by season, and the correlation between the residuals of these equations and the male and female credit equations are also allowed to vary seasonally. In addition, we do not discriminate among

[10] There are a very small number of individuals who belonged to credit programs that met in other villages. For example, there are some women in the sample who belonged to Grameen Bank groups even though there was not a Grameen Bank group in their village. These participation decisions were treated as exogenous in the analysis. There are also a few households in which both an adult male and adult female belonged to a credit group although this is nominally prohibited.

[11] Our method is a substantial generalization of the LIML likelihoods presented in Smith and Blundell (1986) and Rivers and Vuong (1988) for limited dependent variables.

the three credit programs in the estimates below. Our earlier work found no significant difference in the effects of borrowing from BRDB, BRAC and the Grameen Bank on labor supply or household consumption.

4. <u>Data, Survey Design and the Definition of Variables</u>

A multi-purpose quasi-experimental household survey was conducted in 87 villages of 29 thanas in rural Bangladesh during 1991-92. The sample consists of 29 thanas (subdistricts) randomly drawn from 391 thanas in Bangladesh, of which 24 had one (or more) of the three credit programs under study in operation, while 5 thanas had none of them.

Three villages in each program thana were then randomly selected from a list of villages, supplied by the program's local office, in which the program had been in operation at least three years. Three villages in each non-program thana were randomly drawn from the village census of the Government of Bangladesh. A household census was conducted in each village to classify households as *target* (i.e., those who qualify to join a program) or *non-target* households, as well as to identify program participating and non-participating households among the target households. A stratified random sampling technique was used to over-sample households participating in one of the credit programs and target nonparticipating households. Of the 1,798 households sampled, 1,538 were target households and 260 non-target households. Among the target households, 905 households (59 percent) were credit program participants.

There are six partly overlapping seasons delineated in the Bangla calendar and three major rice-based seasons are prominent. The survey of households and communities was designed to reflect this pattern of seasonality. The survey was carried out in three rounds corresponding to the *Aus*, *Aman* and *Boro* cropping seasons. The first round of the survey was conducted during the months of December/January, during the post-harvest of *Aman* rice. The second round of survey was carried out during the months of April/May to cover the post-harvest season of *Boro* rice. The third round of the survey was carried out during the months of July/August to cover the post-harvest of *Aus* rice. In our sample survey data, season one refers to the *Aman* season, season two refers to *Boro* season, and the season three refers to the *Aus* season.

The strong seasonality of crop production in Bangladesh is well known to affects the timing of income flows. The *Aman* rice is the largest crop in Bangladesh agriculture and, hence, its production and harvest has the largest impact on agricultural employment, income and prices. Both *Boro* and *Aus* also provide enhanced opportunities for employment but not in the same scale as *Aman.* As the use of high yielding varieties and irrigation technologies has spread, *Boro* crop production has increased in recent years. Nonetheless, the period of least food consumption for the rural poor has traditionally taken place in the months just before the *Aman* harvest. The food availability on per capita basis is the highest during the months just after the *Aman* harvest (November-December), and also during May-June, just after the harvest of *Boro* rice (Chowdhury 1989).

Agricultural employment also responds to seasonal variations in the demand for labor in various crop-related activities. The *Aman* harvest during the months of November-December is characterized by the greatest demand for agricultural labor. The labor demand is also relatively high in the months of January and March, when the transplantation of Boro HYV takes place. Labor demand is lowest during the months of September-October just before the harvest of *Aman* rice. This seasonality in labor demand is mirrored by the seasonal pattern of agricultural employment and wages, and consequently, in the seasonal consumption landless households who depend heavily on wage employment. (Muqtada 1975; Hossain 1990).

Our measure of sharecropping and fixed rental is decimals (a decimal is one one-hundredth of an acre) of agricultural land sharecropped <u>in</u> and rented <u>in</u> during each season, respectively. Our measure of male agricultural wage and self-employment labor is hours in the past month at the time of each seasonal survey round. Table 1 presents the weighted mean and standard deviations of all the dependent variables used in the regressions, by season. Because the samples drawn are not representative of the village population, the means of the variables are adjusted by appropriate weights based on the actual and sample distribution of the households covered in the study villages. The exogenous variables include measures of the age and education of male and female adults in the household, land ownership, sex of the head, and a set of variables indicating the existence of nonresident relations of various type who are landowners. These types of households are potential sources of transfers which may importantly substitute for credit. Appendix Table A1 provides the definitions, means and standard deviations of all the exogenous variables plus female and male program credit. Appendix Table A2 provides data on female hours in the past month in self-employment and wage agriculture (as defined), and demonstrates its relative unimportance as compared to male hours in these activities.

5. Econometric Results

At least four different estimates of the effect of group-based micro-credit on the composition of agricultural contracts are presented. There are two estimates based on the sampled household's eligibility for these programs based upon the actual responses to our 1991/92 village census and the literal application of the 0.5 acre eligibility rule, and two estimates that allow for mistargeting to be an empirically relevant problem for up to double the one-half acre of owned cultivable land permitted *de jure* to join these programs. That is, we arbitrarily reassign households with cultivable land ownership between 0.5 and 1.0 acres and which are not program participants to the program *choice* category from the *no choice* category, and treat their nonparticipation or participation as an endogenous choice. As Pitt (1999) demonstrates, even if some or all of the households were actually prevented from joining because of their ownership of land, that is, even if there were no mistargeting among these households and they could not in fact choose to join these programs, one still obtains consistent estimates of the parameters, albeit with some possible loss of efficiency. In any case, the results below are substantially unaffected by the choice of *de facto* eligibility rule.

Two estimates of each behavioral equation are presented for the 0.5 acre targeting rule and either two or three for the 1.0 acre targeting rules. The first estimate assumes the endogeneity of all six credit variables, and instruments them appropriately using the WESML-LIML-FE framework set out above. The second imposes the exogeneity of a credit variable whenever the relevant test statistic could not reject the null hypothesis of exogeneity. If the results of this exogeneity test differ as between the 0.5 acre and 1.0 acre targeting rules, we present a third estimate using the exogeneity restrictions of the 0.5 acre targeting rule applied to the model with the 1.0 acre targeting rule. The reason for this extra estimate is to permit some inference concerning the extent to which estimates differ as a consequence of the targeting rule or as a consequence of the different exogeneity restrictions imposed. The test statistic for exogeneity of each credit variable (defined by gender of credit recipient and season of agricultural behavior) is a simple t-test that the correlation coefficient D associated with that credit variable is not different from zero. Imposing that a D is equal to zero imposes the exogeneity of the associated credit variable. The critical value for the t-ratio adopted is 1.95. Imposing exogeneity on the basis of these statistical tests yields more efficient parameter estimates and hence our discussion of the magnitude and statistical precision of the credit parameters will always refer to these partially endogenous results.

These dependent variables are substantially censored (a large proportion of observations are zero), particularly fixed rental and sharecropping. As a consequence, the marginal effect of a change in a regressor C on a latent dependent variable (suppressing the subscripts) $E[y^*]$=X$ + C* + : is simply *, but may differ from the effects of C on a random observation. The expected value of y when it might be censored at zero is:

$$E[y|X,C,\mu] \;=\; \Phi(X\beta \;+\; C\delta \;+\; \mu)(X\beta \;+\; C\delta \;+\; \mu + \sigma\lambda)$$

where

$$\lambda \;=\; \frac{\phi((X\beta \;+\; C\delta \;+\; \mu)/\sigma)}{\Phi(X\beta \;+\; C\delta \;+\; \mu)/\sigma)}$$

and N and M are the standard normal probability density function and cumulative density function, respectively, and F is the variance of the regression residual ,. The marginal effect of changes in C on this expectation are

$$\frac{\partial E[y|X,C,\mu]}{\partial C} \;=\; \delta\,\Phi(\frac{X\beta \;+\; C\delta \;+\; \mu}{\sigma}).$$

A simple and effective approximation to the normal cumulative density function M((X$ + C* + :)/F) at the mean of any subsample is the proportion of those engaged with behavior y > 0 in the subample. Table 1 provides the required information to adjust the elasticity of the latent value of any behavior y with respect to program credit, *, to the elasticity of the expectation of any behavior conditional on the regressors. As these are all log-log regression, the parameters on credit correspond to the latent elasticities. The frequency of zero is some of the behaviors studied also made the application of village fixed effects problematic. If no household rented in land in a village, the fixed effect for that village goes to minus infinity. To avoid this outcome, we apply thana fixed effects rather than village fixed effects. There are three sample villages in every sample thana, and all three villages have the same credit program by sample design.[12]

Before discussing these estimation results, it is useful to briefly summarize the effects of these credit programs on the seasonal patterns of total labor supply (wage labor plus all self-employment labor) for women and men, as well as the value of household per capita consumption, as reported in Pitt and Khandker (1999). The strong seasonality of labor supply and household consumption is evident in the simple seasonal tabulations presented in that paper, and reproduced as Appendix Table A3 below. Women's *Aman* season labor supply is about 25 percent higher than *Boro* and *Aus* season labor supply. Men's labor supply is highest in the Aman season, 5 percent lower in the Boro season, and 8 percent lower than in the Aus season. The imperfect ability of households to smooth consumption is also apparent. Average consumption in our 1991/92 sample is highest in the Aman season, is only 2.5 percent lower in the Boro season but is a striking 22.5 percent lower in the *Aus* season.

That paper estimates the effects of program credit on consumption expenditure in which credit effects and D's are allowed to vary by season. Those estimates provide striking evidence of the importance of seasonality in evaluating the effect of credit programs on the poor. The only statistically significant correlation coefficients (D) are for the low consumption *Aus* season. Apparently, self-selection into these credit programs with respect to consumption expenditure arises only from heterogeneity in *Aus* consumption expenditure. The largest female and male credit effects are during the lean *Aus* season. In the *Boro* and *Aus* season, men's credit has small positive but statistically insignificant effects on their labor supply. In addition, the pattern of correlation coefficients (D) reflects this seasonal pattern. There is a large positive correlation coefficient between men's credit residuals and labor supply residuals for the *Aman* season, but small negative D's for the other seasons. Men with higher than average demands on their time during the *Aman* season (conditional on the regressors), the time of peak labor demand, are more like to self-selection themselves into these credit programs and borrow from them, with the

[12]Pitt et. al. (1998) demonstrate that estimates of the effect of these credit program on the nutritional status of children using thana fixed effects are similar to village fixed effects estimates.

consequence of reduced market labor supply during that peak season. No significant differences in the effect of credit on women's labor supply by season were found, consistent with the view that there is likely to be less seasonality in the time allocation of women given the small share of market time in total time.

Table 2 presents estimates of the effect of credit, by gender of program participant, on the sharecropping in of land (in decimals) by season. Exogeneity of credit provided women on sharecropping in the *Boro* and *Aus* seasons is rejected for both eligibility rules and this is reflected in the estimates of the partially endogenous models. The negative signs of these two correlation coefficients suggest that households that sharecrop less than average (conditional on the observed regressors including thana fixed effects), are more likely to have women become program participants. In addition, female borrowing is associated with a statistically significant increase in sharecropping during the *Boro* and *Aus* seasons. Female credit has a statistically insignificant effect on sharecropping in the *Aman* season, and male credit has statistically insignificant effects on sharecropping in every season. These results are qualitatively unaffected when the 1.0 eligibility rule is used. The overall effect is clear – female credit increases this particular form of agricultural contract, one that typically requires mostly household labor for cultivation. The magnitude of the effect of female program credit on sharecropping in of land is quite large. The latent elasticity is nearly 0.7 (with the 0.5 acre rule) during the Aus season and about 0.45 during the *Boro* season. Note that the season in which sharecropping is least, is the season in which the increase in sharecropping due to microcredit is greatest.

This pattern of credit effects by seasonal is in accord with the seasonal patterns found in Pitt and Khandker (1999). *Aus* is the lean season, with strikingly lower consumption than in the peak *Aman* season. *Aus* is also the season in which males supply the least total market labor supply (see Table A3). It is during this difficult season that credit has its largest effect on increasing own-cultivation through sharecropping. Moreover, this is essentially only an effect of women's credit. As noted in the introductory section, unlike men's credit, women's credit is less likely to induce men to substitute nonagricultural labor time for agricultural labor time. Women's credit-financed self-employment is less likely to provide a competing use for male time, and by diversifying household income, it permits the household to choose riskier but higher yielding agricultural contracts.

Table 3 presents estimates of the effect of credit on fixed rental of land by season. As Table 1 demonstrates, the rental of land is fairly unimportant in our sample compared to other contractual relations in agriculture. Less than 10 percent of all household-seasons in every subsample in Table 1 engage in the fixed rental of land. The D's presented in the first column of Table 3 are not significantly different from zero in every case. With exogeneity imposed, all of the credit effects are positive but only the effect of male credit on *Boro* season fixed rental is statistically difference from zero. The estimates with the 1.0 acre eligibility rule are slightly different, but this difference is almost entirely due to different exogeneity restrictions rather than the any bias that might arise from possible mistargetting. Woman's credit is not endogenous in the determination of fixed rental in the *Aus* season, although it is only slightly larger in absolute value than in the base eligibility case. With the exogeneity of all other credit variables imposed, the effect of male credit on *Boro* season fixed rental is now marginally significant but there is a negative and marginally significant (t=-1.868) negative impact of female credit on *Aus* fixed rental area. There is very little difference between the fully exogenous model for fixed rental under the 1.0 acre rule compared to the 0.5 acre rule. Unlike the strong positive female credit effects on sharecropping, there is no clear pattern of credit effects on fixed rental.

The much larger average importance of sharecropping as compared to fixed rental for functionally landless households implies that the net effect of these credit programs is to increase own-cultivation of agricultural crops. The labor supply effect of this increase in own-cultivation is made clear in Table 4. Credit provided both females and males positively and significantly increase the hours that males spend in the own-cultivation of field crops in every season. Moreover, Table 5 reveals that male wage labor in agriculture is negatively and significantly reduced in every season by both female and male credit except for male credit in the peak *Aman* season. As Table 1d demonstrates, among target nonparticipating households, male agricultural wage labor supply is almost twice as large as self-employment in agriculture. However, male agricultural wage labor supply is only 19 percent larger then self-employment in agriculture among target participating households. The regression estimates suggest that program credit is causally responsible for much of this difference by inducing a substitution away from agricultural wage labor in favor of self-employment in agriculture. The elasticity of latent male self-employment hours with respect to male credit is as high as 0.15 during the *Aus* season and not less than 0.10 in any season. The elasticity of latent male self-employment hours with respect to female credit is highest in the *Aman* season (0.14) and not less than 0.06 in any season. Where are these hours coming from? Certainly from agricultural wage labor. The elasticity of latent male wage labor in agriculture hours with respect to male credit is -0.17 in the *Aus* season and -0.12 in the *Boro* season.[13] The elasticity of latent male wage labor in agriculture hours with respect to female credit is negative and statistically significant in every season, with the largest magnitude in Aman.

Differences in the effect of credit by gender of participant on male agricultural labor supply have a less clear cut pattern than for sharecropping. Male credit has the greatest relative positive effect on self-employment in agriculture in the slack season (*Aus*), and the least (but still positive) relative effect in the peak season (*Aman*). In addition, male credit has the greatest relative effect on reducing wage employment in agriculture in the slack season (*Aus*), and increases wage agricultural employment in the peak season (*Aman*). Thus, the biggest shifts of labor occur during the slack season which is when the biggest credit-induced increases in sharecropping take place. However, it was female rather than male credit that had the largest influence on increasing land contracted in for self-cultivation. Female credit does increase *Aus* male agricultural self-employment hours (and reduce agricultural wage hours) in accord with the increase in tenancy, but does so even more in the Aman season, although it is likely that this difference in not statistically significant. The net effect of credit on male hours is to reduce them overall and smooth them over the seasons (Pitt and Khandker (1998 and 1999).

6. Summary

This paper examines the effect of group-based credit for the poor in Bangladesh on the mix of agricultural contracts and the supply of agricultural labor at the household level. Specifically, it examines the effect of group-based micro-finance, by gender of participant, on

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[13]This elasticity is positive, although not significantly different from zero, in the *Aman* peak season.

male hours of wage labor, male hours of self-employment in agriculture, and the area of land the household cultivates that is sharecropped and rented. The risky nature of agricultural and the need to smooth consumption, coupled with absent or incomplete markets for insurance and credit, importantly determine the mix of agricultural activities that households undertake in rural South Asia. Landless cultivators are more likely to have their contractual choices shaped by credit market constraints than others.

Earlier work has demonstrated that the need to smooth consumption seems to be an important determinant of program participation, and that participation is quite effective at smoothing both household consumption and the labor supply of males across the seasons. This enhanced ability to smooth consumption should permit households to choose riskier but higher yielding contracts available to them for all of their other activities. One might also believe that woman's credit might have a different impact on the mix of agricultural contracts and on male agricultural labor supply than male credit. Male program credit, if properly monitored, should cause men to substitute away from supplying agricultural labor and contracting for agricultural land to supplying the nonagricultural labor required by the financed nonagricultural self-employment activity. Furthermore, since women are otherwise much less involved in income-generating activities, women's program participation diversifies the sources of household income not merely by the type of activity undertaken but diversifies it across individuals within the household. The effect of health and other person-specific shocks on the smoothness of consumption is lessened when a household diversifies income generation across it's members.

We find strong evidence that participation in these group-based micro-credit programs substantially alters the mix of agricultural contracts chosen by participating households. In particular, there is a significant increase in own-cultivation through sharecropping coupled with a complementary increase in male hours in field crop self-employment and a reduction in male hours in the wage agricultural labor market. We find no strong effect of program credit on the fixed rental of land, a type of contractual relationship that is not common among the landless poor in Bangladesh. Female credit effects are larger than male credit effects in increasing sharecropping. In addition, female credit acts to increase sharecropping relatively more in the slack (*Aus*) season than in the peak (*Aman*) season. Female credit also reduces male agricultural wage hours in every season. Male credit reduces it in every season except the peak (*Aman*) season. Female and male credit in every season increase self-employment in every season. Thus, it would appear that both female and male credit induce a substitution of male agricultural activity from the wage labor market to own-cultivation, consistent with its effect in diversifying income and smoothing consumption, outcomes that permit households to choose higher return but riskier agricultural contracts.

REFERENCES

Binswanger, Hans P. and Mark R. Rosenzweig, 1993. "Wealth, Weather Risk and the Composition of Agriculture Investments," The Economic Journal, January.

Chowdhury, Omar H., 1989. Analytical Bibliography on Rural Development: A Critical Review of Studies on Nutrition in Rural Bangladesh, Bangladesh Institute of Development Studies.

Hossain, Akhtar, 1990. “Real Wage Determination in Bangladesh Agriculture: An Econometric Investigation” Applied Economics, vol. 22:1549-1565.

Manski, Charles F. and S. R. Lerman, 1977. “The Estimation of Choice Probabilities from Choice-Based Samples,” Econometrica, 45, 1977-1988.

Moffitt, R., 1991. "Program Evaluation with Nonexperimental Data," Evaluation Review 15, 291-314.

Muqtada, M., 1975. “The Seed-fertilizer technology and surplus labor in Bangladesh Agriculture” Bangladesh Development Studies, vol. 3:403-28.

Pitt, Mark M. 1999. “Does Microfinance Really Help the Poor?: Response to Morduch,” Brown University manuscript, September.

Pitt, Mark M. and Shahidur Khandker, 1998. “The Impact of Group-Based Credit Programs on Poor Households in Bangladesh: Does the Gender of Participants Matter?” Journal of Political Economy, 958-996.

Pitt, Mark M. and Shahidur R. Khandker, 1999. “Credit Programs for the Poor and Seasonality in Rural Bangladesh”, Brown University manuscript, revised March.

Pitt, Mark M. and Shahidur R. Khandker, Omar Haider Chowdhury and Daniel Millimet. 1998. “Credit Programs for the Poor and the Nutritional Status of Children in Rural Bangladesh”, Brown University manuscript, revised December 1998.

Rashid, Mansoora and Robert M. Townsend, 1993. “Targeting Credit and Insurance: Efficiency, Mechanism Design and Program Evaluation,” manuscript, June.

Rivers, Douglas and Quang Vuong, 1988. "Limited Information Estimators and Exogeneity Tests for Simultaneous Probit Models," Journal of Econometrics 39, 347-366.

Smith, R.J. and R.W. Blundell, 1986. "An Exogeneity Test for a Simultaneous Equation Tobit Model with an Application to Labor Supply," Econometrica 54, 679-685.

Table 1

Weighted Means and Standard Deviations of Dependent Variables

a. Full Sample

Dependent Variables	Mean	Std. Deviation	Obs.	No. engaged in activity
Sharecropped agricultural land (decimals)	16.00	49.18	5345	1060
Season 1 (Aman)	24.25	65.80	1798	474
Season 2 (Boro)	14.29	43.92	1778	341
Season 3 (Aus)	9.33	37.60	1769	245
Rented agricultural land (decimals)	3.82	19.32	5345	464
Season 1 (Aman)	6.37	22.67	1798	235
Season 2 (Boro)	3.35	18.81	1778	153
Season 3 (Aus)	1.70	15.46	1769	76
Male agric. wage labor (hours per month	63.78	123.50	5345	1790
Season 1 (Aman)	65.46	125.59	1798	1146
Season 2 (Boro)	71.67	131.06	1778	1150
Season 3 (Aus)	54.75	112.51	1769	1259
Male self-employ. in agric. (hours per month)	72.28	130.04	5345	2509
Season 1 (Aman)	90.72	152.27	1798	891
Season 2 (Boro)	69.95	127.60	1778	829
Season 3 (Aus)	55.87	102.74	1769	789

b. Nontarget households

Dependent Variables	Mean	Std. Deviation	Obs.	No. engaged in activity
Sharecropped agricultural land (decimals)	14.25	47.70	4567	922
Season 1 (Aman)	20.52	60.11	1538	403
Season 2 (Boro)	13.52	43.13	1519	300
Season 3 (Aus)	8.60	35.45	1510	219
Rented agricultural land (decimals)	3.04	15.74	4567	390
Season 1 (Aman)	4.97	20.37	1538	191
Season 2 (Boro)	2.71	13.92	1519	131
Season 3 (Aus)	1.40	11.17	1510	68
Male agric. wage labor (hours per month	81.37	137.00	4567	1670
Season 1 (Aman)	85.50	140.47	1538	609
Season 2 (Boro)	88.19	141.95	1519	586
Season 3 (Aus)	70.29	127.42	1510	475
Male self-employ. in agric. (hours per month)	36.09	90.20	4567	1890
Season 1 (Aman)	44.61	106.00	1538	677
Season 2 (Boro)	36.66	92.16	1519	626
Season 3 (Aus)	26.80	66.76	1510	587

c. Credit program participating households

Dependent Variables	Mean	Std. Deviation	Obs.	No. engaged in activity
Sharecropped agricultural land (decimals)	16.78	53.93	2696	566
Season 1 (Aman)	23.77	70.75	905	236
Season 2 (Boro)	16.51	50.30	897	187
Season 3 (Aus)	10.00	32.94	894	143
Rented agricultural land (decimals)	3.62	17.05	2696	243
Season 1 (Aman)	5.61	20.27	905	123
Season 2 (Boro)	3.76	17.17	897	82
Season 3 (Aus)	1.48	12.54	894	38
Male agric. wage labor (hours per month	68.42	132.23	2696	837
Season 1 (Aman)	69.81	132.22	905	303
Season 2 (Boro)	77.79	141.15	897	303
Season 3 (Aus)	57.63	121.99	894	231
Male self-employ. in agric. (hours per month)	51.85	111.44	2696	1217
Season 1 (Aman)	99.72	157.97	905	421
Season 2 (Boro)	76.47	131.54	855	395
Season 3 (Aus)	61.72	108.53	894	401

d. Target nonparticipating households

Dependent Variables	Mean	Std. Deviation	Obs.	No. engaged in activity
Sharecropped agricultural land (decimals)	12.64	43.19	1871	356
Season 1 (Aman)	18.47	52.23	633	167
Season 2 (Boro)	11.61	37.74	622	113
Season 3 (Aus)	7.70	36.98	616	76
Rented agricultural land (decimals)	2.66	14.83	1871	147
Season 1 (Aman)	4.56	20.44	633	68
Season 2 (Boro)	2.03	11.32	622	49
Season 3 (Aus)	1.34	10.20	616	30
Male agric. wage labor (hours per month)	89.64	139.36	1871	833
Season 1 (Aman)	95.40	144.65	633	306
Season 2 (Boro)	94.84	142.14	622	283
Season 3 (Aus)	78.46	130.23	616	244
Male self-employ. in agric. (hours per month)	25.96	71.59	1871	673
Season 1 (Aman)	31.79	83.75	633	256
Season 2 (Boro)	27.17	73.51	622	231
Season 3 (Aus)	18.71	53.12	616	186

Table 2

Alternative Estimates of the Impact of Credit on Sharecropping by Season
(hundreth's of acres)

Explanatory Variables	Eligibility based on 0.5 acre		Eligibility based on 1.0 acre	
Amount borrowed by female x season 1 (Aman)	0.69555E-02 (0.123)	0.16727 (0.714)	0.92241E-01 (0.342)	-0.31385E-01 (-0.590)
Amount borrowed by female x season 2 (Boro)	0.41664 (2.551)	0.45589 (2.393)	0.42066 (2.071	0.39214 (2.267)
Amount borrowed by female x season 3 (Aus)	0.66647 (3.834)	0.69731 (3.665)	0.67278 (4.089)	0.65293 (4.398)
Amount borrowed by male x season 1 (Aman)	0.40275E-01 (0.694)	-0.15177 (-0.680)	-0.15462 (-0.519)	-0.48810E-02 (-0.086)
Amount borrowed by male x season 2 (Boro)	0.62133E-01 (1.042)	-0.82461E-01 (-0.380)	-0.14071E-01 (-0.047)	0.27831E-01 (0.472
Amount borrowed by male x season 3 (Aus)	0.11472 (1.853)	-0.39065E-01 (-0.217)	0.30005E-01 (0.141)	0.84030E-01 (1.357)
D(women, season 1)	-0.17854 (-0.840)		-0.13092 (-0.523)	
D(women, season 2)	-0.36644 (-2.548)	-0.33815 (-2.607)	-0.35456 (-2.303)	-0.33359 (-2.453)
D(women, season 3)	-0.50597 (-3.900)	-0.49011 (-3.872)	-0.49970 (-4.698)	-0.48969 (-4.815)
D(men, season 1)	0.21219 (0.922)		0.16686 (0.543)	
D(men, season 2)	0.16097 (0.751)		0.41595E-01 (0.141)	
D(men, season 3)	0.16898 (0.997)		0.54977E-01 (0.285)	
Log likelihood	-8659.33	-8661.62	-8810.34	-8811.07
Observations with choice/ total observations	3815/5218	3815/5218	3938/5218	3938/5218

Note: Figures in parentheses are asymptotic t-ratios

Table 3

Alternative Estimates of the Impact of Credit on the Fixed Rental by Season
(hundreth's of acres)

Explanatory Variables	Eligibility based on 0.5 acre		Eligibility based on 1.0 acre		
Amount borrowed by female x season 1 (Aman)	0.82556E-01 (0.331)	0.57224E-01 (0.836)	0.76472E-01 (0.288)	0.26608E-01 (0.388)	.0417 (0.615)
Amount borrowed by female x season 2 (Boro)	0.31700E-01 (0.142)	0.66108E-01 (0.865)	-0.72225E-01 (-0.315)	0.36427E-01 (0.485)	.0512 (0.619)
Amount borrowed by female x season 3 (Aus)	-0.22996 (-1.144)	0.70820E-02 (0.100)	-0.31091 (-1.705)	-0.29974 (-1.868)	-.0084 (-0.088)
Amount borrowed by male x season 1 (Aman)	0.73778E-01 (0.207)	0.16388E-01 (0.223)	0.23520 (0.727)	-0.93680E-02 (-0.121)	.0023 (-.031)
Amount borrowed by male x season 2 (Boro)	0.33546 (1.142)	0.17398 (2.163)	0.34379 (0.988)	0.15082 (1.916)	.1572 (2.013)
Amount borrowed by male x season 3 (Aus)	0.38130 (1.385)	0.96917E-01 (0.996)	0.34825 (1.048)	0.98120E-01 (1.023)	.0812 (0.847)
D(women, season 1)	-0.36109E-01 (-0.170)		-0.55401E-01 (-0.249)		
D(women, season 2)	0.26297E-01 (0.145)		0.11945 (0.615)		
D(women, season 3)	0.29845 (1.634)		0.36673 (2.285)	0.35258 (2.520)	
D(men, season 1)	-0.57132E-01 (-0.176)		-0.22155 (-0.866)		
D(men, season 2)	-0.16032 (-0.659)		-0.16895 (-0.590)		
D(men, season 3)	-0.24713 (-1.183)		-0.22041 (-0.880)		
Log likelihood	-6599.92	-6602.10	-6762.76	-6764.05	-6766.19
Observations with choice/total observations	3815/5218	3815/5218	3938/5218	3938/5218	3938/5218

Note: Figures in parentheses are asymptotic t-ratios

Table 4

Alternative Estimates of the Impact of Credit on Male Self-employment in Agriculture by Season (log hours per month)

Explanatory Variables	Eligibility based on 0.5 acre		Eligibility based on 1.0 acre		
Amount borrowed by female x season 1 (Aman)	0.15236 (2.033)	0.14301 (2.248)	0.10688 (1.351)	0.16312E-01 (0.601)	0.1013 (1.519)
Amount borrowed by female x season 2 (Boro)	0.92650E-01 (1.556)	0.59816E-01 (2.042)	0.54616E-01 (0.872)	0.27336E-01 (0.976)	0.0321 (1.127)
Amount borrowed by female x season 3 (Aus)	0.79698E-01 (1.301)	0.75434E-01 (2.678)	0.40677E-01 (0.611)	0.42701E-01 (1.566)	.0475 (1.719)
Amount borrowed by male x season 1 (Aman)	0.11534 (1.603)	0.10524 (3.483)	0.11420 (1.345)	0.82319E-01 (2.763)	.0793 (2.676)
Amount borrowed by male x season 2 (Boro)	0.12142 (1.989)	0.12749 (4.047)	0.11431 (1.620)	0.94950E-01 (3.097)	.0969 (3.160)
Amount borrowed by male x season 3 (Aus)	0.16769 (2.154)	0.14694 (4.940)	0.17938 (2.150)	0.11586 (3.960)	.1178 (4.020)
D(women, season 1)	-0.21891 (-1.948)	-0.20501 (-2.147)	-0.17262 (-1.452)		-.1646 (-1.643)
D(women, season 2)	-0.64058E-01 (-0.784)		-0.42251E-01 (-0.487)		
D(women, season 3)	-0.49101E-02 (-0.055)		0.14357E-01 (0.146)		
D(men, season 1)	-0.18420E-01 (-0.162)		-0.63291E-01 (-0.473)		
D(men, season 2)	0.11299E-01 (0.133)		-0.30516E-01 (-0.307)		
D(men, season 3)	-0.40259E-01 (-0.330)		-0.11431 (-0.899)		
Log likelihood	-11945.16	-11945.57	-12138.21	12140.41	-12138.92
Observations with choice/total observatins	3815/5218	3815/5218	3938/5218	3938/5218	3938/5218

Note: Figures in parentheses are asymptotic t-ratios

Table 5

Alternative Estimates of the Impact of Credit on Male Wage Employment in Agriculture by Season (log hours per month)

Explanatory Variables	Eligibility based on 0.5 acre		Eligibility based on 1.0 acre	
Amount borrowed by female x season 1 (Aman)	-0.16416 (-0.348)	-0.14795 (-3.308)	-0.14503 (-0.289)	-0.13437 (-3.007)
Amount borrowed by female x season 2 (Boro)	-0.20210 (-0.499)	-0.10061 (-2.253)	-0.21221 (-0.504)	-0.89516E-01 (-2.015)
Amount borrowed by female x season 3 (Aus)	-0.26199 (-0.828)	-0.10683 (-2.289)	-0.29438 (-0.971)	-0.96310E-01 (-2.070)
Amount borrowed by male x season 1 (Aman)	0.20525 (1.267)	0.15361 (1.129)	0.20783 (1.157)	0.15455 (1.020)
Amount borrowed by male x season 2 (Boro)	0.80069E-01 (0.467)	-0.12428 (-2.308)	0.11814 (0.641)	-0.11436 (-2.157)
Amount borrowed by male x season 3 (Aus)	0.14473E-01 (0.082)	-0.16609 (-2.770)	0.50922E-02 (0.027)	-0.15758 (-2.663)
D(women, season 1)	0.73608E-02 (0.015)		-0.23950E-02 (-0.005)	
D(women, season 2)	0.11091 (0.258)		0.13216 (0.298)	
D(women, season 3)	0.18335 (0.573)		0.23209 (0.763)	
D(men, season 1)	-0.32524 (-2.369)	-0.27477 (-2.351)	-0.30555 (-1.981)	-0.25391 (-1.927)
D(men, season 2)	-0.23173 (-1.498)		-0.25615 (-1.565)	
D(men, season 3)	-0.19389 (-1.245)		-0.16823 (-0.995)	
Log likelihood	-10841.71	-10845.50	-10993.16	-10998.14
Observations with choice/total observations	3815/5218	3815/5218	3938/5218	3938/5218

Note: Figures in parentheses are asymptotic t-ratios

Table A1

Weighted Means and Standard Deviations of Independent Variables and Credit[a]

Independent Variable	Mean	Std. Dev.
Parents of HH head own land?	0.256	0.564
Brothers of HH head own land?	0.815	1.308
Sisters of HH head own land?	0.755	1.208
Parents of HH head's spouse own land?	0.529	0.784
Brothers of HH head's spouse own land?	0.919	1.427
Sisters of HH head's spouse own land?	0.753	1.202
Household land (in decimals)	76.142	108.54
Highest grade completed by HH head	2.486	3.501
Sex of household head (1=male)	0.948	0.223
Age of household head (years)	40.821	12.795
Highest grade completed by any female HH member	1.606	2.853
Highest grade completd by any male HH member	3.082	3.081
Adult male not present in HH?	0.035	0.185
Adult female not present in HH?	0.017	0.129
Spouse not present in HH?	0.126	0.332
Value of program borrowing by females (Taka)[b] (779 households)	5498.85	7229.351
Value of program borrowing by males (Taka)[b] (631 households)	3691.993	7081.581

[a]Sample size : 87 villages, 1757 households, 9215 individuals.
[b] Endogenous variable. Amount borrowed is the cumulative amount of credit borrowed since December 1986 from any of these three credit programs adjusted to 1992 prices.

Table A2

Female Agricultural Wage and Self-Employment Labor Supply
(Hours in past month)

Dependent Variables	Mean	Std. Deviation	Obs.	No. engaged in activity
Female agric. wage hours: full sample	3.23	25.40	5345	125
Season 1 (Aman)	3.88	28.49	1798	57
Season 2 (Boro)	4.09	27.02	1778	46
Season 3 (Aus)	1.70	19.72	1769	22
Female agric. wage hours: target households	4.50	30.12	5345	121
Season 1 (Aman)	5.79	34.61	1798	57
Season 2 (Boro)	5.43	31.07	1778	43
Season 3 (Aus)	2.26	23.38	1769	21
Female self-employ. in agric hours: full	4.99	31.40	5345	290
Season 1 (Aman)	11.21	48.78	1798	172
Season 2 (Boro)	2.62	19.15	1778	76
Season 3 (Aus)	1.06	11.64	1769	42
Female self-employ. in agric hours: target	2.93	20.15	5345	230
Season 1 (Aman)	6.29	30.02	1798	135
Season 2 (Boro)	1.98	15.76	1778	63
Season 3 (Aus)	0.45	6.48	1769	32

Table A3
Weighted Means and Standard Deviations of Total Women's and Men's Labor Supply and Per Capita Expenditure

Dependent Variables	Partici-pants	Obs.	Non-participants	Obs.	Total	Obs.	Nonprog. areas	Obs.	Aggregate	Obs.
Women's labor supply (hours per month, ages 16-59 years)	40.328 (70.478)	3420	37.680 (71.325)	2108	38.905 (70.934)	5528	43.934 (74.681)	1074	39.540 (71.432)	6602
Season 1 (Aman)	44.515 (73.961)	1157	40.559 (72.661)	720	41.8555 (73.088)	1877	29.121 (67.761)	365	39.825 (72.401)	2242
Season 2 (Boro)	37.904 (68.590)	1139	28.998 (59.067)	698	31.950 (62.504)	1837	29.728 (52.228)	357	31.587 (60.939)	2194
Season 3 (Aus)	38.492 (68.549)	1124	27.693 (59.213)	690	31.290 (62.664)	1814	35.001 (59.895)	352	31.901 (62.519)	2166
Men's labor supply (hours per month, ages 16-59 years)	202.758 (100.527)	3534	185.858 (104.723)	2254	191.310 (103.678)	5788	180.94 (98.805)	1126	189.477 (102.902)	6914
Season 1 (Aman)	209.389 (107.000)	1201	196.037 (112.121)	769	200.330 (110.640)	1970	184.352 (101.847)	383	197.526 (109.296)	2353
Season 2 (Boro)	201.849 (96.821)	1173	181.772 (100.899)	746	188.267 (100.007)	1919	190.737 (96.384)	372	188.704 (99.530)	2291
Season 3 (Aus)	196.848 (96.942)	1160	179.435 (99.808)	739	185.055 (99.193)	1899	167.651 (95.853)	371	181.961 (98.810)	2270
Per capita HH total expenditure (Taka)	77.014 (41.496)	2696	85.886 (64.820)	1650	82.959 (58.309)	4346	89.661 (66.823)	872	84.072 (59.851)	5218
Season 1 (Aman)	87.673 (50.837)	905	95.162 (63.754)	557	92.706 (59.901)	1462	84.038 (50.555)	295	91.268 (58.530)	1757
Season 2 (Boro)	79.407 (39.808)	897	88.857 (59.411)	548	85.732 (53.883)	1445	111.152 (94.469)	290	89.965 (63.177)	1735
Season 3 (Aus)	63.872 (26.470)	894	73.413 (34.459)	545	70.253 (58.695)	1439	73.707 (34.459)	287	70.826 (55.419)	1726

Note: Standard deviations are in the parentheses. Source: Pitt and Khandker (1999)