The Bangladesh Development Studies
Vol. XXVI, June-Sept. 2000, Nos. 2 & 3

The Effect of Non-agricultural Self-employment Credit on Contractual Relations and Employment in Agriculture: The Case of Microcredit Programmes in Bangladesh

by
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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 labour which takes the form of own-cultivation as opposed to agricultural wage labour. The group-based microcredit programmes examined provide production credit for non-agricultural 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 gender of participant. Male programme credit, if properly monitored, should induce men to substitute away from supplying agricultural labour and contracting for agricultural land to supplying the non-agricultural labour required by the non-agricultural self-employment activity financed by the microcredit programme. Programme 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. These 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 microcredit programmes substantially alters the mix of agricultural contracts chosen by participating households. In particular, both female and male participation induces 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 labour 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 labour and increasing agricultural self-employment, as predicted.

I. 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 labour. By "mix of agricultural contracts" we mean

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the quantities of land sharecropped and rented, and the extent to which agricultural labour supply takes the form of own-cultivation as opposed to agricultural wage labour. 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 labour 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 labour 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 labour 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) labour in the agricultural labour market—whose returns are subject to these weather shocks and weather induced seasonality[1]. The group-based microcredit programmes examined below provide production credit for non agricultural activities to essentially assetless rural households. These households can reduce their exposure to weather-related uncertainties by diversifying into activities that respond less to weather shocks and seasonal weather patterns. These non-agricultural activities, by diversifying income sources, may also lead households to choose riskier, but higher average return, agricultural contracts— choosing more to be cultivators than sellers of labour in the market.

This paper estimates the impact of participation in three group-based microfinance programmes (Grameen Bank, Bangladesh Rural Advancement Committee (BRAC), and Bangladesh Rural Development Board's (BRDB) Rural Development RD-12 programme), by gender of participant, on the mix of agricultural contracts, measured as male hours of wage labour, 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 microcredit programmes 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 labour market. We find no strong effect of programme 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 mircocredit financed non-agricultural self- employment projects induce households to choose higher risk agricultural contracts. The implication that higher risk contracts are associated with higher returns is consistent with the findings of Pitt and Khandker (1999) that microcredit increases household consumption as well as smooths it across the seasons.

II. MICROCREDIT, SEASONALITY, AND RISK

In recent years, governmental and non-governmental organizations in many low-income countries have introduced credit programmes targeted at the poor. Many of these programmes specifically target women based on the view that they are more likely to be credit constrained than men, have restricted access to the wage labour

[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 labour supply is relatively small even among the landless. This is illustrated with our survey data.

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 programmes for the poor, and over 90 per cent of its clients are women.

All three of the Bangladesh programmes examined below work exclusively with the rural poor. Although the sequence of delivery and the provision of inputs vary some from programme to programme, all three programmes essentially offer production credit to the landless rural poor (defined as those who won 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. Programmes 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]

The majority of borrowers from the microcredit programmes studied in this paper use their loans to finance non-farm activities and, during the time period covered by our data, lending by microcredit programmes to finance field crop agriculture was prohibited. If smoothing consumption is an important motivation for poor rural households, they are likely to chose 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 microcredit programmes, can also help households free up other sources of financing that can be used as working capital or to smooth consumption directly.

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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 Bank has offered housing loans to group members as well.

[3] As part of Grameen Bank's social development programme, 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 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".

The three group-based credit programmes (Grameen Bank, Bangladesh Rural Advancement Committee (BRAC), and Bangladesh Rural Development Board's (BRDB) Rural Development RD-12 programme) examined are the major microcredit programmes in Bangladesh. Participation in these groups 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 groups 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 cannot substitute somewhat for consumption credit or for prohibited agricultural credit. If a household wishes to devote resources obtained from savings, inter-household transfers, or money borrowed from lenders or other sources to a production activity in the absence of group-based credit, it may, in the presence of group-based lending programmes, 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 of agricultural contracts, as well as smooth consumption. Access to group-based microcredit may enhance the household's ability to borrow from other sources or obtain transfers, which may make it more likely to undertake the own-cultivation of field crops, increase self-employment in field crop agriculture, and reduce labour supply to the agricultural labour market.

In an earlier paper using the same data as here, Pitt and Khandker (1998) find that participation in these credit programmes, 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 labour supply and household consumption. They also rejected the hypothesis that programme credit is exogenous in the determination of many of these outcomes. That is, unobserved variables that affect credit programme participation (as measured by borrowing) also affect these outcomes, such as consumption and men's labour supply, conditional on credit programme participation. In that paper, seasonality in behaviour is treated by including seasonal dummy variables in the conditional demand equations.

In subsequent work, Pitt and Khandker (1999) allow for the effects of programme credit to vary by season by including season-credit interactions. If smoothing consumption across seasons is an important motivation for participating in these credit programmes, households with more seasonal fluctuations in consumption and labour supply than average would be more likely to participate. This suggests that the correlation between the unobserved determinants of programme credit and consumption and labour supply may vary seasonally in intensity. In particular, Pitt and Khandker (1998) found that there was a significant negative correlation between programme 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 programmes. If seasonal consumption smoothing were a motivation for credit programme 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 programmes 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 programmes. Thus, the need to smooth consumption seems to be an important determinant of programme participation. Moreover, Pitt and Khandker (1999) demonstrate that participation is indeed quite effective at smoothing both household consumption and the labour 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 labour 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 female credit has a different impact on the mix of agricultural contracts and on male agricultural labour supply than does male credit. Male programme credit, if properly monitored, should cause men to substitute away from supplying agricultural labour and contracting for agricultural land to supplying the non-agricultural labour required by the non-agricultural self-employment activity financed by the microcredit programme. Furthermore, since women are otherwise much less involved in income-generating activities, women's programme 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 its members.

III. ESTIMATION METHODS

A. Identification from a Quasi-experiment

The econometric methods used in the analysis are 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 behaviours, conditioned on the household's programme participation as measured by the quantity of credit borrowed.[4] Leaving seasonal considerations aside for the moment, consider the reduced from equation (1) for the level of participation in one of the credit programmes (C_{ij}), where level of participation will be taken to be the value of programme credit that household *i* in village *j* borrows:

$$C_{ij} = X_{ij}\beta^c + Z_{ij}\pi + \mu_j^c + \varepsilon_{ij}^c \qquad (1)$$

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 behaviours 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 non-systematic error that reflects unmeasured determinants that vary over households.

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

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

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 non-systematic error reflecting, in part, unmeasured determinants of

[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 programmes. These programmes are more than just lending institutions. Nevertheless, the quantity of credit is the most obvious and well measured of the services provided.

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 programme 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 programme. If credit programme placement across the villages of Bangladesh is attentive to the village effects μ_j, identifying programme effects by comparing households in non-programme villages with households in programme villages without controlling for the selectivity of programme placement will generally result in biased estimates of programme effects. Using a village fixed effects estimation technique may remove the source of correlation between programme placement and the behaviour of interest, however, without further exogenous variation in programme 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, δ, the effect of participation in a credit programme on the outcome y_{ij}, can be identified if the sample also includes households in villages with treatment choice *(programme 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 *cultivable* land are precluded from joining any of the three credit programmes.[6]

There are a number of households in our sample that are programme participants yet had more than 0.5 acres of land at the time of programme entry, raising the possibility of mis-targeting and

[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).

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 programme 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 programme participants owning less than 0.5 acres of cultivable land at the time of joining. This suggests that programme officers are using some notion of "effective" units of cultivable land in determining eligibility rather than of the type of mis-targeting 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 mis-targeting. 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 mis-targeting, each of the 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 programme 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 behaviour y_{ij} in addition to any treatment effect from the programme. The conditional demand equation is:

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

The exogeneity of land ownership is the assumption that $E(X_{ij}, \varepsilon_{ij}^y)=0$, 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 programme. It is clear that all the parameters, including the effect of the credit programme δ, is identified from this design. In particular, the estimator of the programme effect δ is a variant of the differences-in-the-differences estimator widely applied in the general programme evaluation literature. To see this, note that an estimate of δ is obtained from the following difference-in-the-difference: [7]

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

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 non-linearity 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-programme village and households residing in a programme 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:

$$\log L(\beta, \delta, \mu, \rho) = \sum_{\mathit{Choice}} \log\Phi_2((\mu_p^c + X\beta_c)\, d_c,\ (\mu_p^y + X\beta_y + \delta I_c) d_y,\ \rho d_c d_y)$$

$$+ \sum_{\substack{\mathit{no\ choice} \\ \mathit{programme\ village}}} \log\Phi((\mu_p^y + X\beta_y)\, d_y) + \sum_{\substack{\mathit{non\text{-}programme} \\ \mathit{village}}} \log\Phi((\mu_n^y + X\beta_y)\, d_y) \quad (5)$$

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 programme in programme villages, μ_p^y are village-specific effects influencing the binary outcome I_y in programme villages, μ_n^y are the corresponding village-specific effects in non-programme 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 programme credit are not identifiable for villages that do not have programmes.

[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) through (4d).

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

The first part of the likelihood is the joint probability of programme participation and the binary outcome I_y conditional on participation for those households that are both eligible to join the programme *(choice)* and reside in a village with the programme *(programme village)*. This part of the likelihood corresponds to the expectation (4d). Without regressors (Z) that influence the probability of programme 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^y_p and β_y from this part of the likelihood. The second part of the likelihood is the (univariate) probability of binary outcome I_y for landed households in programme villages and corresponds to expectation (4c). These households are precluded from joining the programme 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 programme 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 β_y in (3) is identified from variation in landholding within the programme villages (j=2) and a sample of non-programme 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 non-target 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/ non-target 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 programme (which requires meeting the land ownership rule and residing in a village with a credit programme) and all the exogenous variables of the model, X_{ij} and μ_j. Consequently, the model is not non-parametrically identified. That is, if the linear indices $X_c \gamma$ and $(X_y \beta + \delta I_c)$ in (5) were replaced by non-parametric 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 behaviour is affected differently by credit if the programme participant is a woman or a man. For that reason, the reduced form credit equation is disaggregated by gender :

$$C_{ijf} = X_{ij}\beta_{cf} + \mu^{c}_{if} + \varepsilon^{c}_{ijf} \tag{6}$$

$$C_{ijm} = X_{ij}\beta_{cm} + \mu^{c}_{jm} + \varepsilon^{c}_{ijm} \tag{7}$$

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:

$$y_{ijs} = X_{ijs}\beta_y + \mu^{y}_{j} + \alpha_s + \sum_s C_{ifj}\, D_{jfs}\, \delta_{fs} + \sum_s C_{ijm}\, D_{jms}\, \delta_{ms} + \varepsilon^{y}_{ijs} \tag{8}$$

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 programmes with possibly different effects on behaviour. Identification of gender-specific credit is achieved by making use of another quasi-experimental attribute of these programmes and the survey. All programme 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 programme, and some households from villages with only male credit groups, so that landless females are denied programme choice.[9] In particular, of the 87 villages in the sample, 15 had no credit programme, 40 had credit-groups for both females and males, 22 had female-only groups and 10 had male-only groups. 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.

necessary assumption is that the availability of a credit group by gender in a village is uncorrelated with the household errors ε^{y}_{ij} conditional on X_{ij} and the village fixed effects μ_j. As each village had only one type of credit programme available, and it is assumed that the type of credit programme (BRDB, BRAC, or Grameen Bank) is uncorrelated with the household errors ε^{y}_{ij} conditional on X_{ij} and the village fixed effects μ_j, there is no need to model which of the programmes' members of a household join.[10]

While the likelihood given by (5) illustrates the general principle and method used, the actual likelihoods maximized have been altered to allow for other aspects of our data. Male and female credit, and most of the dependent variables (male hours of wage labour, 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 IV). In particular, programme 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.

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[10] There are a very small number of individuals who belonged to credit programmes 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 specifications of the conditional 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 the three credit programmes in the estimates below. Our earlier work found no significant difference in the effects of borrowing from BRDB, BRAC, and the Grameen Bank on labour supply or household consumption.

IV. DATA, SURVEY DESIGN, AND THE DEFINITION OF VARIABLES

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 (sub-districts) randomly drawn from 391 thanas in Bangladesh, of which 24 had one (or more) of the three credit programmes under study in operation, while 5 thanas had none of them.

Three villages in each programme thana were then randomly selected from a list of villages, supplied by the programme's local office, in which the programme had been in operation at least three years. Three villages in each non-programme thana were randomly drawn from the village census of the Government of Bangladesh. A households census was conducted in each village to classify households as *target* (i.e. those who qualify to join a programme) or *non-target* households, as well as to identify programme 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 programmes and target non-participating households. Of the 1,798 households sampled, 1,538 were target households and 260 non-target households. Among the target households, 905 households (59 per cent) were credit programme 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 the 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 season three refers to the *Aus* season.

The strong seasonality of crop production in Bangladesh is well known to affect 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 on 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 labour in various crop-related activities. The *Aman* harvest during the months of November-December is characterized by the greatest demand for agricultural labour. The labour demand is also relatively high in the months of January and March, when the transplantation of *Boro* HYV takes place. Labour demand is lowest during the months of September-October just before the harvest of *Aman* rice. This seasonality in labour demand is mirrored by the seasonal pattern of agricultural employment and wages, and consequently, in the seasonal consumption of 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 *in* and rented *in* during each season, respectively. Our measure of male agricultural wage and self-employment labour is hours in the past month at the time of each seasonal survey round. Table I 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 non-resident relations of various type who are landowners. These types of households are potential sources of transfers which may importantly substitute for credit. Table A.1 provides the definitions, means, and standard deviations of all the exogenous variables plus female and male programme credit. Table A.2 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.

V. ECONOMETRIC RESULTS

At least four different estimates of the effect of group-based microcredit on the composition of agricultural contracts are presented. There are two estimates based on the sampled household's eligibility for these programmes 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 mis-targeting to be an empirically relevant problem for up to double the one-half acre of owned cultivable land permitted *de jure* to join these programmes. That is, we arbitrarily reassign households with cultivable land ownership between 0.5 and 1.0 acres and which are not programme participants to the programme *choice* category from the *no choice* category, and treat their non-participation 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 mis-targeting among these households and they could not in fact choose to join these programmes, 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 a *de facto* eligibility rule.

Two estimates of each behavioural 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 behaviour) is a simple t-test of the hypothesis that the correlation coefficient ρ associated with that credit variable is not different from zero. Imposing that a ρ 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) $E[y^*] = X\beta + C\delta + \mu$ is simply δ, 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:

$$E[y \mid X, C, \mu] = \Phi(X\beta + C\delta + \mu)(X\beta + C\delta + \mu + \sigma\lambda) \qquad (9)$$

where,

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

and ϕ and Φ are the standard normal probability density function and cumulative density function, respectively, and σ is the variance of the regression residual ε. The marginal effect of changes in C on this expectation are :

$$\frac{\partial E[y \mid X, C, \mu]}{\partial C} = \delta\,\Phi\left(\frac{X\beta + C\delta + \mu}{\sigma}\right) \qquad (10)$$

A simple and effective approximation to the normal cumulative density function $\Phi\ (X\beta + C\delta + \mu)/(\sigma)$ at the mean of any subsample is the proportion of those engaged with behaviour $y>0$ in the subsample. Table I provides the required information to adjust the elasticity of the latent value of any behaviour y with respect to programme credit, δ, to the elasticity of the expectation of any behaviour conditional on the regressors. As these are all log-log regression, the parameters on credit correspond to the latent elasticities. The frequency of zero in some of the behaviours 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 programme by sample design.[12]

Before discussing these estimation results, it is useful to briefly summarize the effects of these credit programmes on the seasonal patterns of *total* labour supply (wage labour plus *all* self-employment labour) 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 labour supply and household consumption is evident in the simple seasonal tabulations presented in that paper, and reproduced as Table A.3. Women's *Aman* season labour supply is about 25 per cent higher than *Boro* and *Aus* season labour supply. Men's labour supply is highest in the *Aman* season, 5 per cent lower in the *Boro* season, and 8 per cent 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 per cent lower in the *Boro* season but is a striking 22.5 per cent lower in the *Aus* season.

That paper estimates the effects of programme credit on consumption expenditure in which credit effects and ρ's are allowed to vary by season. Those estimates provide striking evidence of the importance of seasonality in evaluating the effect of credit programmes on the poor. The only statistically significant correlation coefficients(ρ) are for the low consumption *Aus* season. Apparently, self-selection into these credit programmes 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 labour supply. In addition, the pattern of correlation coefficients (ρ) reflects this seasonal pattern. There is a large positive correlation coefficient between men's credit residuals and labour supply residuals for the *Aman* season, but small negative ρ'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 labour demand, are more likely to

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

self-select themselves into these credit programmes and borrow from them, with the consequence of reduced market labour supply during that peak season. No significant differences in the effect of credit on women's labour 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 II presents estimates of the effect of credit, by gender of programme 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 programme 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 labour for cultivation. The magnitude of the effect of female programme 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 season 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 labour supply (see Table A.3). 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 non-agricultural labour time for agricultural labour 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 III presents estimates of the effect of credit on fixed rental of land by season. As Table I demonstrates, the rental of land is fairly unimportant in our sample compared to other contractual relations in agriculture. Less than 10 per cent of all household-seasons in every sub-sample in Table I engage in the fixed rental of land. The ρ's presented in the first column of Table III 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 different 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 any bias that might arise from possible mis-targeting. Female 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 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 programmes is to increase own-cultivation of agricultural crops. The labour supply effect of this increase in own-cultivation is made clear in Table IV. Credit provided to both females and males positively and significantly increases the hours that males spend in the own-cultivation of field crops in every season. Moreover, Table V reveals that male wage labour 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 Id demonstrates, among target non-participating households, male agricultural wage labour supply is almost twice as large as self-employment in agriculture. However, male agricultural wage labour supply is only 19 per cent larger than self-employment in agriculture among target participating households. The regression estimates suggest that programme credit is causally responsible for much of this difference by inducing a substitution away from agricultural wage labour in favour 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 labour. The elasticity of latent male wage labour 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 labour 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 labour 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 increasing wage agricultural employment in the peak season (*Aman*). Thus, the biggest shifts of labour 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; 1999).

VI. 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 labour at the household level. Specifically, it examines the effect of group-based microfinance, by gender of participant, on male hours of wage labour, 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

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

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 programme participation, and that participation is quite effective at smoothing both household consumption and the labour 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 female credit might have a different impact on the mix of agricultural contracts and on male agricultural labour supply than male credit. Male programme credit, if properly monitored, should cause men to substitute away from supplying agricultural labour and contracting for agricultural land to supplying the non-agricultural labour required by the financed non-agricultural self-employment activity. Furthermore, since women are otherwise much less involved in income-generating activities, women's programme 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 its members.

We find strong evidence that participation in these group-based microcredit programmes 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 labour market. We find no strong effect of programme 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 labour 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.

TABLE I

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 Labour (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

(Contd.)

TABLE I *(Contd.)*

b. Non-target 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 Labour (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

(Contd.)

TABLE I *(Contd.)*

c. Credit Programme 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 Labour (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

(Contd.)

TABLE I *(Contd.)*

d. Target Non-participating 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 Labour (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 II

ALTERNATIVE ESTIMATES OF THE IMPACT OF CREDIT ON SHARECROPPING OF LAND 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)	0.0069585 (0.123)	0.16727 (0.714)	0.092241 (0.342)	−0.031385 (−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)	0.040275 (0.694)	−0.15177 (−0.680)	−0.15462 (−0.519)	−0.0048810 (−0.086)
Amount Borrowed by Male X Season 2 (Boro)	0.062133 (1.042)	−0.082461 (−0.380)	−0.014071 (−0.047)	0.027831 (0.472)
Amount Borrowed by Male X Season 3 (Aus)	0.11472 (1.853)	−0.039065 (−0.217)	0.030005 (0.141)	0.084030 (1.357)
ρ (Women, Season 1)	−0.17854 (−0.840)		−0.13092 (−0.523)	
ρ (Women, Season 2)	−0.36644 (−2.548)	−0.33815 (−2.607)	−0.35456 (−2.303)	−0.33359 (−2.453)
ρ (Women, Season 3)	−0.50597 (−3.900)	−0.49011 (−3.872)	−0.49970 (−4.698)	−0.48969 (−4.815)
ρ (Men, Season 1)	0.21219 (0.922)		0.16686 (0.543)	
ρ (Men, Season 2)	0.16097 (0.751)		0.041595 (0.141)	
ρ (Men, Season 3)	0.16898 (0.997)		0.054977 (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 III

ALTERNATIVE ESTIMATES OF THE IMPACT OF CREDIT ON THE FIXED RENTAL OF LAND BY SEASON

(HUNDRETH'S OF ACRES)

Explanatory Variables	Eligibility Based on 0.5 Acres		Eligibility Based on 1.0 Acre		
Amount Borrowed by Female X Season 1 (Aman)	0.082556	0.057224	0.076472	0.026608	0.0417
	(0.331)	(0.836)	(0.288)	(0.388)	(0.615)
Amount Borrowed by Female X Season 2 (Boro)	0.031700	0.066108	–0.072225	0.036427	0.0512
	(0.142)	(0.865)	(–0.315)	(0.485)	(0.619)
Amount Borrowed by Female X Season 3 (Aus)	–0.22996	0.0070820	–0.31091	–0.29974	–0.0084
	(–1.144)	(0.100)	(–1.705)	(–1.868)	(–0.088)
Amount Borrowed by Male X Season 1 (Aman)	0.073778	0.016388	0.23520	–0.0093680	0.0023
	(0.207)	(0.223)	(0.727)	(–0.121)	(–0.031)
Amount Borrowed by Male X Season 2 (Boro)	0.33546	0.17398	0.34379	0.15082	0.1572
	(1.142)	(2.163)	(0.988)	(1.916)	(2.013)
Amount Borrowed by Male X Season 3 (Aus)	0.38130	0.096917	0.34825	0.098120	0.0812
	(1.385)	(0.996)	(1.048)	(1.023)	(0.847)
(Women, Season 1)	–0.036109		–0.055401		
	(–0.170)		(–0.249)		
ρ (Women, Season 2)	0.026297		0.11945		
	(0.145)		(0.615)		
ρ (Women, Season 3)	0.29845		0.36673	0.35258	
	(1.634)		(2.285)	(2.520)	
ρ (Men, Season 1)	–0.057132		–0.22155		
	(–0.176)		(–0.866)		
ρ (Men, Season 2)	–0.16032		–0.16895		
	(–0.659)		(–0.590)		
ρ (Men, Season 3)	–0.24713		–0.22041		
	(–1.183)		(–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 IV

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)	0.016312 (0.601)	0.1013 (1.519)
Amount Borrowed by Female X Season 2 (Boro)	0.092650 (1.556)	0.059816 (2.042)	0.054616 (0.872)	0.027336 (0.976)	0.0321 (1.127)
Amount Borrowed by Female X Season 3 (Aus)	0.079698 (1.301)	0.075434 (2.678)	0.040677 (0.611)	0.042701 (1.566)	0.0475 (1.719)
Amount Borrowed by Male X Season 1 (Aman)	0.11534 (1.603)	0.10524 (3.483)	0.11420 (1.345)	0.082319 (2.763)	0.0793 (2.676)
Amount Borrowed by Male X Season 2 (Boro)	0.12142 (1.989)	0.12749 (4.047)	0.11431 (1.620)	0.094950 (3.097)	0.0969 (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)	0.1178 (4.020)
ρ (Women, Season 1)	–0.21891 (–1.948)	–0.20501 (–2.147)	–0.17262 (–1.452)		–1646 (–1.643)
ρ (Women, Season 2)	–0.064058 (–0.784)		–0.042251 (–0.487)		
ρ (Women, Season 3)	–0.0049101 (–0.055)		0.014357 (0.146)		
ρ (Men, Season 1)	–0.018420 (–0.162)		–0.063291 (–0.473)		
ρ (Men, Season 2)	0.011299 (0.133)		–0.030516 (–0.307)		
ρ Men, Season 3)	–0.040259 (–0.330)		–0.11431 (–0.899)		
Log Likelihood	–11945.16	–11945.57	–12138.21	12140.41	–12138.92
Observations with Choice/Total Observations	3815/5218	3815/5218	3938/5218	3938/5218	3938/5218

Note : Figures in parentheses are asymptotic t-ratios.

TABLE V

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)	−0.089516 (−2.015)
Amount Borrowed by Female X Season 3 (Aus)	−0.26199 (−0.828)	−0.10683 (−2.289)	−0.29438 (−0.971)	−0.096310 (−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)	0.080069 (0.467)	−0.12428 (−2.308)	0.11814 (0.641)	−0.11436 (−2.157)
Amount Borrowed by Male X Season 3 (Aus)	0.014473 (0.082)	−0.16609 (−2.770)	0.0050922 (0.027)	−0.15758 (−2.663)
ρ (Women, Season 1)	0.0073608 (0.015)		−0.0023950 (−0.005)	
ρ (Women, Season 2)	0.11091 (0.258)		0.13216 (0.298)	
ρ (Women, Season 3)	0.18335 (0.573)		0.23209 (0.763)	
ρ (Men, Season 1)	−0.32524 (−2.369)	−0.27477 (−2.351)	−0.30555 (−1.981)	−0.25391 (−1.927)
ρ (Men, Season 2)	−0.23173 (−1.498)		−0.25615 (−1.565)	
ρ (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.

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Appendix

TABLE A.1

WEIGHTED MEANS AND STANDARD DEVIATIONS OF INDEPENDENT VARIABLES AND CREDIT[a]

Independent Variables	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 Completed 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 Programme Borrowing Females (Taka)b (779 Households)	5498.85	7229.351
Value of Programme 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 programmes adjusted to 1992 prices.

TABLE A.2

FEMALE AGRICULTURAL WAGE AND SELF-EMPLOYMENT LABOUR 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 Sample	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 Households	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 A.3

WEIGHTED MEANS AND STANDARD DEVIATIONS OF TOTAL WOMEN'S AND MEN'S LABOUR SUPPLY AND PER CAPITA EXPENDITURE

Dependent Variables	Participants	Obs.	Non-participants	Obs.	Total	Obs.	Non-prog. Areas	Obs.	Aggregate	Obs.
Women's Labour 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 Labour 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).