Wider impacts of microcredit: evidence from labor and human capital in urban Mexico

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Abstract

This paper presents an estimation of the impacts of microcredit on labor and human capital following a quasi-experiment specifically designed to control for endogeneity and selection bias in the context of urban Mexico. We find important indirect trickle-down effects of credit through labor expenditure that benefit poor laborers; however, these effects were only observed when loan-supported enterprising households reached a level of income well above the poverty line. We also find significant, although small impacts of credit on children´s schooling that could be potentially reinforced by improvements in lending technology, school grants and additional ex-ante preventive and ex-post protective risk-coping products.

JEL Classification: C24; C25; C81; O16; O17; O18
Keywords: microcredit; labor; children´s schooling; Mexico

Introduction

The relationship between credit and labor is particularly important in the context of urban poverty. For the moderately poor and non-poor, income-generating activities are often important sources of income, whereas for the extreme poor, labor is, in many cases, the only source of livelihoods. Thus, by improving access to credit, a *direct* impact on *labor intensity* could be observed even beyond the household, with *indirect* impacts on poor laborers that are *hired* by loan-supported enterprising households. This can be crucial for the extreme poor, since in the urban context farming activities are rarely existent. Higher levels of labor intensity could, however, increase the propensity of child labor from young family members, and thus compromise *wider* impacts on human capital and long-run patterns of development. We explore all these wider impacts using data collected from households participating in three microcredit programs operating in Mexico. The paper is organized as follows: Section 1 presents the analytical framework where the relationship between credit and efficiency labor is analyzed. Section 2 describes the quasi-experimental research designed followed to control for endogeneity and selection bias, while in section 3 we discuss the econometric procedure to test for the underlying assumptions of no endogeneity and selection problems. Sections 4 and 5 examine the impact of microcredit on labor intensity, and labor hiring, respectively, whereas section 6 analyzes the impacts on children´s schooling. Section 7 concludes with some policy recommendations.

1. Credit and efficiency labor

We begin the discussion by considering the case of an enterprising household engaged in an income generating activity that produces a market good *y*, based on a Cobb-Douglas-type production function $y = f(L, K)^{\alpha}$, where L and K are the quantity of labor and capital, respectively, and α is a parameter of technology in the production of *y*. As pointed out by Pitt and Khandker (1998), it is very unlikely that at the bottom end of the income distribution α changes, at least in the short-term. For that reason, we assume that technology remains constant, i.e. $\alpha = 1$.

In the production of *y*, the enterprising household will supply the amount of labor L^H, restricted to a *maximum* of hours-work, *h,* conditional upon the number N of household members of working age *i*, in the form of $L^H \geq \underset{i,h}{\text{Max}}\, \text{N}\left[i(h)\right]$. In this sense, under self-employment, $L = L^H$. Since we assume that α remains constant, then an increase in the level of output, coming from a capital injection of a microcredit, will lead to an increase in *labor intensity*, which once reaching the maximum of L^H, may lead to labor hiring.

Note, however, that the demand for labor is not only a function of household income but also of the *cost of labor*. As pointed out by Leibenstein (1957); Mazumdar (1959) and Dasgupta (1993), *labor efficiency* is conditional upon factors such nutrition, abilities and efforts that determine *labor productivity*. Informational asymmetries may also play an important role in that process (see e.g. Foster and Rosenzweig 1996, and Bardhan and Rudra 1986). Dasgupta and Ray (1986) have actually pointed out that at low levels of household income, even if an enterprising household wants to hire laborers, they soon realize that they can only afford to hire unskilled and malnourished laborers with very low productivity.

They may also perceive it to be very risky to employ workers for not having enough information about their skills, behavior or moral integrity. In the end, the enterprising household may simply decide to self-employ, leading to an increasing propensity of child labor from young family members, with negative impacts human capital and on long-run patterns of development.

Thus, the cost of buying an efficiency unit of labor is given by $\mu = w / \lambda(w)$, where w is the wage rate, and $\lambda(w)$ captures *labor efficiency*. Note that $\lim_{w/\lambda(w)\to\infty} f(\lambda) = 0$. Households will only consider hiring labor when they have reached a certain level of income, $\bar{Y}$, where the cost of an *efficiency unit of labor* is at its maximum, i.e. $\bar{\mu} = \max[w / \lambda(w)]$ [ii]. The quantity of labor hired is measured by the expenditure on efficiency labor, $L^h \lambda(w)$, where L^h is the units of labor hired.

At very low levels of household income, from 0 to $\bar{Y}$ in the upper quadrant of figure 1, no household hires workers given the high cost of buying an efficiency unit of labor (the area above $\bar{\mu}$) and they remain self-employed, (from 0 to L^H in the lower quadrant). Once the enterprising household reaches the level of earnings $\bar{Y}$, as a result of higher production, they begin hiring laborers with a minimum level of skills, abilities, and so on, that represent a maximum cost of efficiency labor, $\bar{\mu}$, that the household is willing to absorb. Thus, if $\bar{\mu}$ is affordable, then $L^h > 0$ and $L = L^H + L^h$. Note that the further the distance from $\bar{Y}$ to Y, i.e. the higher the household income, the lower the cost of buying additional efficiency units of labor μ, and thus, the higher the probability of reporting labor expenditure, $W = L^h \lambda(w)$. If by borrowing from a microcredit program, an enterprising household increases the probability of an income rise, then we may observe an *indirect impact* of credit on poor laborers whose skills and nutrition levels are improved by the fact of being employed by an enterprising household. This could potentially lead to improvements in *labor efficiency*.

INSERT FIGURE 1 ABOUT HERE

2. Research design

In order to investigate the relationship between credit and labor, we designed a type of quasi-experiment that is often referred to as *a non-equivalent, post test-only quasi-experiment* (Campbell and Stanley 1966), in which two groups of households are sampled: treatment and control. A major problem that emerges with the *non-equivalent, post test only quasi-experiment*, referred hereafter as *quasi-experiment*, is that these two groups may differ in important ways that influence the decision of borrowing and thus, the outcome of interest. In other words, there might be unobservable factors related to e.g. individual efforts, abilities, preferences and attitudes towards risk that cause a *demand-related bias*. A fundamental assumption here is that participation in a microcredit program is *always* voluntary. But even if we had a control group willing to take risks and borrow from a microcredit organization, we may still face *selectivity discrimination* made by the lender or group members that screen out applicants for e.g. living faraway from the place where the microcredit program operates, a *supply-related bias.*

Although we did not observe households that chose either to participate or not, and households that were either accepted or rejected by the lender, we were able to specify the distribution of households that self-selected to participate in a microcredit program, and were accepted by the lender with a time-variance difference that accounts for the *length of membership*. Consequently, households who had self-selected to participate in a credit program and had been accepted by the lender, and therefore were actively borrowing from a microcredit program were eligible to be sampled as members of the *treatment group.* Similarly, households who had self-selected to participate in a credit program and had been accepted by the lender, but had not received a loan by the time the quasi-experiment was conducted, were eligible to be sampled as members of the *control group*.

We also followed a *geographical criterion*, i.e. we operationalised the quasi-experiment among households living in the same neighborhood, in areas with a minimum level of socio-economic homogeneity, where the comparison between treatment and control groups was reasonable. By following this sampling strategy, it was possible to hold constant factors such as infrastructure, costs of inputs, and local prices that could cause, otherwise, an *endogeneity* problem. A high population density in poor urban areas made possible to follow this approach. As a result, we assume that the *selection* and *endogeneity* problems are controlled through the process of data collection itself. In section 3 we follow a specific econometric estimation procedure to test for such assumptions.

Given the homogeneity of household characteristics, a sample survey was the preferred type of data collection (Babbie 1990). The sampling strategy was implemented using a *multistage* procedure in the form of clusters (Fink and Kosecoff 1985): first, we had access to a list of program participants (both treatment and control) from three case-study organizations (the clusters), and who lived in the selected areas. Participants with loan in arrears were included in the list. In the second stage, both treatment and control groups were selected at random. The survey was administrated face-to-face employing, as instrument of data collection, a semi-structured-interview format[iii].

In the end, we surveyed 148 households: 55 participating at Community Financial Services (Fincomun) and living in San Miguel Teotongo, a neighborhood located to the eastern periphery of Mexico City; 46 participating at Centre for the Assistance of the Microentrepreneur (CAME) and living in the Chalco Valley, one of the most densely populated municipalities in the country located to the eastern periphery of the Metropolitan area of Mexico City; and 47 participating at Programs for Women (Promujer) and living in Tula City and the surrounding areas, a locality about two hours from Mexico City. Thus, we have three locations, one for each organization (see table 1 for more details).

INSERT TABLE 1 ABOUT HERE

3. Testing for selection bias and endogeneity

Before analyzing the impact of microcredit on labor, we proceed to test for the underlying assumption of no selection bias. In order to do so, we initially considered a Heckman estimation procedure (Heckman 1979) with an identifying instrumental variable (IV)[iv]. This Maximum Likelihood method follows the model:

$$L_i = X_i\beta_L + I_i\delta + u_i^L \tag{1}$$
$$I_i = X_i\beta_I + Z_i\gamma + u_i^I \tag{2}$$

where I_i is a dichotomous variable with value $I=1$ for treatment households and $I=0$ for the corresponding control group. Since both treatment and control groups are program participants with a time-variance difference that accounts for the length of membership, then

$$E\langle L_{1i} \,|\, I_i = 1\rangle - E\langle L_{2i} \,|\, I_i = 0\rangle = X_i\left(\beta_1 - \beta_2\right) + \sigma^* \frac{\phi\left(Z_i\gamma\right)}{\Phi\left(Z_i\gamma\right)} + V \tag{3}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the density of the distribution function and the cumulative distribution function of the standard normal, respectively, and $E(V)=0$. Note that $\sigma^* = (\sigma_{2\varepsilon} - \sigma_{1\varepsilon})$ results from the covariance matrix derived in Maddala (1977) as follows:

$$Cov(u_{1i}, u_{2i}, \varepsilon_i) = \begin{pmatrix} \sigma_{11} & \sigma_{12} & \sigma_{1\varepsilon} \\ \sigma_{12} & \sigma_{22} & \sigma_{2\varepsilon} \\ \sigma_{1\varepsilon} & \sigma_{2\varepsilon} & 1 \end{pmatrix} \tag{4}$$

which enables us to measure the impact of program participation on the outcome of interest, L_i by comparing the expected outcome for treatment and control groups. If $\sigma^* > 0$, then we encounter a significant selection problem.

L_i, which captures the number of units of labor invested per month by enterprising households, including labor-hiring, is in logarithmic form and coded as LGAGHOURSPM. X_i is a vector of household characteristics, and Z_i is an observable variable distinct from those in X_i that affect I_i but not L_i conditional on I_i, that plays the role of the identifying instrument (see table 9 for more details). The instrumental variable must be *partially* correlated with I_i, i.e. the coefficient on Z_i must be nonzero, $\gamma \neq 0$, so $Cov(Z_i, u_i^I) \neq 0$, while Z_i must be uncorrelated with L_i, so $Cov(Z_i, u_i^L) = 0$, where the projected error, $E\left(u_i^L\right) = 0$ is uncorrelated with Z_i. Thus, selecting an appropriate instrument becomes a crucial and complex task for the estimation.

The Heckman procedure (referred hereafter as Heckit) allows testing for the assumption of no self-selectivity by estimating the inverse Mills ratio, $\lambda(\cdot) \equiv \dfrac{\phi(\cdot)}{\Phi(\cdot)}$, resulting from the relationship between the density of the distribution function, $\phi(\cdot)$, and the cumulative distribution function of the standard normal, $\Phi(\cdot)$. As suggested by Heckman (1979), we can estimate consistently the parameters β_I and γ by exploiting the properties of the first-stage Probit estimation and then get the estimated inverse Mills ratio, $\hat{\lambda}$. In the second-stage we obtain the parameters β_y and δ from Ordinary Least Squares (OLS) with the inverse Mills ratio added to the regressors as follows:

$$L_i = X_i \beta_L + I_i \delta + M\lambda + u_i^L \qquad (5)$$

The two-stage Least Square (2SLS) procedure yields consistent estimates in the parameter of interest δ (Wooldridge 2002) where M and λ are the inverse Mills ratio and its parameter estimate, respectively. A simple way of testing for selection bias is under the null hypothesis, $H_0 : \lambda = 0$, using the usual 2SLS t statistic. If $\lambda \neq 0$, then the selection problem is significant.

Note that the slope coefficient δ reports, in the Heckit, the average impact of program participation; however, it does not take into account the effect of borrowing over time. Treatment households with say five years of membership are expected to report greater impacts than those households with just one or two years of membership. This is in part due to the effects of *progressive lending*, an incentive device extensively used by microcredit programs. In order to address this issue, we extend the Heckit procedure to a Tobit selection equation. We do so by replacing the treatment dichotomous variable I_i in equation (2) by a continuous variable, C_i, that measures the amount of credit borrowed during the last credit cycle. We assume that C_i is *exogenously* determined by the lender who defines this maximum threshold according to level of participation in the program. Thus we have the following specification equation:

$$C_i^* = X_i\beta_c + Z_i\gamma + u_i^c \tag{6}$$

where $C_i = \max(0, C_i^*)$, i.e. (7)

$$C_i = C_i^* \quad \text{if} \quad C_i^* > 0 \ \text{(for treatment group)} \tag{8}$$

$$C_i = 0 \quad \text{if} \quad C_i^* \le 0 \ \text{(for control group)} \tag{9}$$

and $u_i \mid X_i \sim Normal(0, \sigma^2)$

Consequently, C_i takes a maximum value and a lower threshold zero in the form of a censored Tobit model (Tobin 1958) with a $C_i > 0$ for treatment groups and $C_i = 0$ for control groups[v]. In this way we believe to capture a more precise measure of the impact of microcredit. Note that the Tobit model implies that the probability of observing $C_i > 0$ and $C_i = 0$ are $\phi(\cdot)$ and $p(C_i^* < 0) = \Phi(0)$, respectively, where $\phi(\cdot)$ and $\Phi(\cdot)$ denote the density function and the cumulative density function of the standard normal. These assumptions are very similar to those implied in the Heckit, but now the log-likelihood function takes the form

$$\ln L = \sum_{C_i > 0}\left(-\ln\sigma + \ln\phi\left(\frac{C_i - X_i\beta_c}{\sigma}\right)\right) + \sum_{C_i = 0}\ln\left(1 - \Phi\left(\frac{X_i\beta_c}{\sigma}\right)\right) \tag{10}$$

which generates the conditional mean function of the observed dependent variable C_i that is *censored at zero* for control groups and have disturbances normally distributed, which can be used to estimate the determinants of the level of borrowing by treatment and control groups alike[vi] through the marginal effects of X_i on C_i as follows[vii]:

$$\frac{\partial E\left[C_i \middle| X_i\right]}{\partial X_i} = \beta_c \Phi\left(\frac{X_i \beta_c}{\sigma}\right) \tag{11}$$

This is actually the reason of using a Tobit specification equation. If no censoring had occurred, the Tobit model would be inappropriate (Maddala 1999). Thus, the borrowing function, on the one hand, takes the form:

$$C_i = \alpha_c + X_i \beta_c + Z_i \gamma + K_i \theta_c + u_i^c \tag{12}$$

where α_c is the intercept; β_c, γ and θ_c are the unknown parameters, and u_i^c, the error term that captures unmeasured household characteristics that determine borrowing levels. The labor equation, on the other hand, conditional upon the level of program participation C_i takes the form:

$$L_i = \alpha_L + X_i \beta_L + K_i \theta_L + C_i \delta + u_i^L \tag{13}$$

where α_L is the intercept and β_L, θ_L and δ are the unknown parameters, and u_i^L, the error term that reflects unmeasured determinants of L_i that vary from household to household. We have included in (12) and (13) a vector of credit market characteristics, K_i, which captures the effects of other credit agents such as moneylenders and rotating savings and credit associations (ROSCAS) that actively compete with microcredit program. The rationale behind incorporating K_i relies on the principle that if we do not control for the effects of such agents on L_i, then the parameter δ may be inconsistent, i.e. we could wrongly attribute some outcomes to the microcredit program when in fact come from, for example, ROSCAS.

Since C_i is included as the impact variable in (13), we need to identify an instrumental variable to control for policy-specifics that affect the credit equation but not the outcome of interest. This instrument must satisfy the same conditions as in the Heckit in order to estimate the 2SLS Tobit procedure, the type of method that Amemiya (1984) refers to as Type III Tobit model. We derive that estimation equation as follows:

$$L_i = \alpha_L + X_i\beta_L + K_i\theta_L + C_i\delta + R_i\upsilon + e_i \qquad (14)$$

where R_i and υ are the predicted Tobit residuals and its parameter estimate, respectively, and $e_i \equiv u_i^L - E(u_i^L | R_i)$, where (e_i, R_i) are assumed to be independent of X_i, i.e. $E(e_i | X_i, R_i) = 0$. The predicted residuals from the Tobit equation are estimated when $C_i \geq 0$ in (12) and then included as another regressor in (14) to yield consistent and efficient estimators (Wooldridge 2002). The null of no selection bias is tested in similar fashion as in the Heckit; however, now we use the 2SLS heteroskedasticity-robust t statistic on the predicted residuals: when $\upsilon \neq 0$, a selection problem is encountered.

3.1 Selecting the instrumental variable

We have identified as the instrument a continuous variable (coded as DISTANCE) that captures the time participants spent since they left home (or business) until they arrived to the branch, and which is used as a proxy of *accessibility* to credit. Our argument relies on the idea that the correlation between program participation and accessibility emerges from two sources: 1) A process involving choice, where households reporting high transaction and opportunity costs of participation would either have high incentives to borrow the largest amount of credit, in order to compensate these costs, or simply drop out or not to participate in the first place. 2) Microcredit programs impose due to transaction costs implicitly related to monitoring and enforcement activities, lending restrictions to households living outside the branch's operational radius[viii].

When equation (12) was estimated with DISTANCE as the identifying instrument, the p-values of the *t* statistic for the coefficient γ rejected the null of $H_0: \gamma = 0$, reflecting the statistically significance correlation between the level borrowing, C_i and the instrument in

Z_i; however, when Z_i was included in equation (13), the parameter estimate γ accepted the null of no correlation against L_i (see table 2)[ix]. As a result, we were able to use DISTANCE in the Tobit selection procedure to test for the underlying assumption of no selection bias.

INSERT TABLE 2 ABOUT HERE

Note that the predicted residuals from the second-stage Tobit selection equation presented in table 3 (and coded as RESID) report insignificant levels in the parameter estimate υ, confirming, as in the parameter estimate λ of the inverse Mills ratio in the Heckit procedure (coded as MILLS), the assumption of no self-selectivity. In this sense, the evidence suggests that increasing levels of borrowing are a function of policy-specifics that are exogenously determined by the lender. We found no evidence to imply that it is due to unobservable factors that are related to individual choice or preferences.

In order to confirm the assumption of exogeneity, we exploit the qualities of the Hausman's procedure (Hausman 1978) by testing under the null hypothesis that the asymptotic covariance matrix of the 2S-Tobit selection equation is not systematically larger than the OLS estimator. In order words, we examine under the null if $p\lim\ \mathbf{d}=0$, where $\mathbf{d}=\mathrm{b}_{2S-Tobit}-B_{OLS}$, whereas under the alternative, $p\lim\ \mathbf{d}\neq 0$. Following Greene (2003:83) we compute the Hausman statistic in STATA as follows:

$$H=(\hat{b}_{2S-Tobit}-\hat{B}_{OLS})'\left\{Est.Asy.\ \mathrm{Var}\left[\hat{b}_{2S-Tobit}\right]-Est.Asy.\ \mathrm{Var}\left[\hat{B}_{OLS}\right]\right\}^{-1}\left(\hat{B}_{OLS}-\hat{b}_{2S-Tobit}\right)\xrightarrow{d}\chi^2(J)$$

The computed Hausman statistic reports a very small value, $\chi^2(13)=0.63$, suggesting that we cannot reject the null that the $\hat{B}_{OLS}$ and $\hat{b}_{2S-Tobit}$ are both consistent, and $\hat{B}_{OLS}$ efficient relative to $\hat{b}_{2S-Tobit}$. In this sense, by following a geographical criterion during the process of data collection, we were able to control for local factors that could potential cause an *endogeneity* problem, allowing us to concentrate on the OLS results discussed below.

4. The impact of microcredit on labor intensity

As both the units of labor, L_i, and the maximum amount of credit, C_i, are in logarithmic form, the parameter estimate δ measures the *elasticities of* (latent) *units of labor in hours invested with respect to credit*. The slope coefficient reports a positive sign and statistical significance at the 5%, although the magnitude of the impact appears to be small. More precisely, the econometric results suggest that if the maximum amount of credit had gone up by one percent, the units of labor invested is predicted to increase in the order of 0.029%, *ceteris paribus*.

For comparative purposes, we have estimated equation (13) with I_i in substitution of C_i, where I_i is the same dichotomous variable used in the Heckit procedure that takes the value $I = 1$ for treatment households, and $I = 0$ for the corresponding control group. In this case, the coefficient of δ reports the difference in the mean log of units of labor, which can be used to estimate the percentage change of units of labor invested by treatment households relative to the control group. In order to do so, we follow Halvorsen and Palmquist (1980) and take the antilog of δ to obtain $(e^{0.233}) = 1.2624$, suggesting that the *median* of units of labor invested by treatment households was higher than that of the control groups by about 26%, *ceteris paribus*.

We are also interested in examining the impacts of credit over time. This is particularly important due to the fact that microcredit programs extensively use progressive lending as an incentive device to mitigate moral hazard and reduce operational costs in the long run.

Our survey collected data about the length of membership, which measures the number of years of program participation. This variable (coded as MEMBERSHIP) takes a value $M_i > 0$ for treatment households and $M_i = 0$ for control groups. However, since we expect M_i to be correlated with the upper limits of progressive lending, we have included M_i in equation (13) in substitution of C_i, where the parameter δ now captures the *semilog* of units of labor invested with respect to the length of membership. In other words, the slope coefficient of M_i measures the constant proportional or relative change in the number of units of labor invested for a given absolute change in the length of program participation.

The results from the estimation equation with M_i as the impact variable are presented in table 3. The coefficient δ reports statistical significance at 1%. Other things held constant at the mean, the number of units of labor invested is predicted to increase at the annual rate of 9.2% after joining the microcredit program. In order to estimate the rate of growth over the period of time that treatment households had participated in the credit program, we compute the *compound* rate of growth using the *antilog* of δ as follows: [(antilog(δ)-1)x100].

Our results predict a compound rate of annual growth in units of labor invested in the order of 9,6%, which is slightly higher than that of 9.2% obtained from the *instantaneous* estimation. Note that the value reported from the constant is equal to 6.2. Since the constant reflects the *log* of units of labor invested at the beginning of program participation, then by taking the antilog of 6.2, we can estimate the average number of hours invested by control households. We predicted this value at approximately 499 hours per month. In this sense, after one year of program participation, an average household would be able to increase the number of units of labor invested in income-generating activities from 499 to 547 hours per month. Our results clearly reflect the involvement of more than one household member in income-generating activities, which as discussed in section 1, could potentially have negative impacts on children´s schooling, or after reaching certain income levels, go beyond the boundaries of the household, and *indirectly* benefit poor laborers. We examine in section 5 the indirect impacts on labor hiring before analyzing the impact on children's schooling in section 6.

5. Indirect impacts on labor hiring

Our sample survey collected a continuous variable, W_i that captures information about labor expenditure. This variable, which is coded as WAGEXP, is essentially the product of the number of units of labor hired by the enterprising household and the wage rate per unit of labor, i.e. $W = L^h \lambda(w)$ x. In an earlier examination of WAGEXP, we found that a large percentage of participating households did not hire labor. In fact, just about 15% of the sample did actually employed laborers. In this sense, we had two groups of households: one reporting a maximum level of labor expenditure, and another consisting of households that did not report information on labor expenditure. Thus, the continuous variable W_i takes a maximum value and a lower threshold zero in the form $W_i = \max(W_i^*, 0)$, where $W_i = W_i^*$ if $W_i^* > 0$ i.e. if households report labor expenditure, and $W_i = 0$ if $W_i^* \leq 0$, i.e. if households do not report labor expenditure. Since we have a *censored* sample, we decided to follow a Tobit specification equation (Tobin 1958) in the form:

$$W_i^* = \alpha_w + Y_i \beta_w + u_i^w \tag{15}$$

where Y_i is a continuous variable that measures household income, and β_w and u_i^w are the slope coefficient and the error term, respectively. Since we have a data-censoring case demanding the latent variable W_i^* to follow a homoskedastic normal distribution, we have transformed WAGEXP into logarithmic form (coded as LGWAGEXP) to make this assumption more reasonable. Note that this model contains similar characteristics of the first-stage Tobit selection equation previously specified in equation (6), where the probability of observing $W_i > 0$ and $W_i = 0$ are $\phi(\cdot)$ and $p(W_i^* < 0) = \Phi(0)$, respectively, and where $\phi(\cdot)$ and $\Phi(\cdot)$ denote the density function and the cumulative density function of the standard normal.

The reason of following a standard Tobit specification equation comes from the fact that we are interested in analyzing the conditional mean function of the observed dependent variable W_i that is censored at zero for enterprising households with no labor-hiring, and with disturbances normally distributed. The use of OLS for the sub-sample for which

$W_i^* > 0$ would have produced an inconsistent estimator β_w since we are using only the data on uncensored observations, causing a downward bias result (Greene 2003).

As both labor expenditure and household income are in logarithmic form, the parameter estimate β in equation (15) measures the elasticity of *latent* expenditure on efficiency labor with respect to household income. In an attempt to capture any *direct* relationship between labor hiring and credit, equation (15) was estimated with the logarithm of the maximum amount of credit borrowed, C_i in substitution of Y_i, as explanatory variable. In this case, the slope coefficient measures the *elasticity of labor expenditure with respect to credit*. For comparative purposes, we also included, separately, I_i and M_i in substitution of C_i in order to examine any direct impact of program participation, and the length of membership, respectively, on labor expenditure. The results from the Tobit equations are presented in table 4.

INSERT TABLE 4 ABOUT HERE

Although the coefficient of C_i reports a positive sign, we did not find any evidence to confirm a *direct* impact of credit on labor expenditure. The same statistical insignificance was found when equation (15) was computed with I_i and M_i, as the impact variables. We find, however, a large elasticity of labor expenditure with respect to household income. Other things held constant, a one percent increase in the level of household income was predicted to give rise to a 7.8 percent in labor expenditure, which supports the hypothesis of an *indirect* impact of credit through an income rise. The large elasticity can be explained by low initial wages relative to household income. If by borrowing capital, enterprising households manage to increase the level of household income, then an increasing probability of labor expenditure is observed. Although the computed elasticities derived from the Tobit equation give us interesting information about the large responsiveness of the labor expenditure-income relationship, it does not tell us at what level of income enterprising households actually hire labor. In order to estimate this income level, we transform the logs of W_i and Y_i into linear variables and then computed equation (15) accordingly. The results are presented in figure 2.

INSERT FIGURE 2 ABOUT HERE

The slope coefficient β now reports the predicted values of an *absolute change* in W_i conditional upon an *absolute change* in Y_i. As we hypothesize graphically in figure 1, at low levels of income, no household will hire workers given the relative high cost of buying efficiency units of labor, and they remain self-employed. Our estimations suggest that after reaching a minimum level of income, $\overline{Y}$, predicted to be in the order of 18,700 pesos or about 1700 dollars per month, enterprising households begin to consider hiring labor. After point $\overline{Y}$, which we envisage as a *platform for employment generation,* the propensity of labor expenditure becomes positive and significant: a one-peso increase in the level of household income was predicted to give rise 29 cents in labor expenditure, *ceteris paribus*.

Note that the estimated income of the employing household is well above the *capability-based* poverty line derived by Sedesol (2002) for urban poverty in Mexico[xi]. It seems that at low levels of income, the cost of hiring units of efficiency labor is too high, either due to low levels of productivity or informational asymmetries. Mosley and Rock (2004:477) have reported qualitative evidence from Africa showing poor enterprising households being reluctant to hire workers due to *"a very considerable perceived risk associated with the initiation of financial relationships going outside the family".* In our study, narrative evidence shows that labor hiring also emerges when the supply of labor from household members reaches its maximum (point L^H in figure 1). Take the following case:

Mr A lives with his mother and two younger sisters in San Miguel Teotongo, in the Iztapalapa District. He has a small grocery shop located in a neighborhood about 40 minutes from his place of residence. He is the only source of household income since his sisters are students, and his mother, responsible for housework and other chores. As a competitive strategy, he decided to offer late opening hours that became afterwards a 24-hours service, 7 days a week. At nights, the main selling products are beer, spirits and food. In order to attend the grocery shop throughout the night, he hired two waged-workers. He pays 850 pesos each (some US $76) for about 40 hours per week. This about 2.2 times the estimated capability based poverty line estimated for urban areas in Mexico.

Based on the data reported by Mr. A, we estimate an average household income in the order of 1728 US dollars per month, which after weighted by equivalence factors (see Rothbarth 1943), yields an income per adult equivalent 3.15 times the capability based poverty line. When we asked Mr. A. the reasons for employing laborers he said: *"The business has been growing and I wanted to open the shop longer hours but I cannot work 24 hours, you know. My sisters and my mother cannot help me either. It is too risky to work at nights. That is why I decided to hire my employees..."* Interview: Int2-01302004.

Although we find no evidence of labor hiring below the *capability-based* poverty line, we did find that 27% of the hired laborers were below a *food-based* poverty line derived by Sedesol (2002), which identifies extreme deprivation in urban areas, and almost 60% were below an *asset-based* poverty line, which has been derived to measure moderate poverty.

The empirical evidence also reports important differences between treatment and control households in relation to the wage paid to laborers relative to the poverty lines. For analytical purposes, we focus on the *capability-based* poverty line. While laborers hired by treatment households received a wage 25% above the poverty line, the corresponding control groups paid a wage far below that threshold of deprivation (about 64.4%). It would seem that there is a positive impact of program participation on laborers' welfare. Evidence from a cross-tabulation show a statistical significant association at the 0.05 level between treatment and control groups in relation to the units of labor hired, measured in hours per week. Workers employed by treatment households worked on the average 34 hours per week vis-à-vis 19.7 hours reported by workers employed by control households (see table 5).

This could ultimately benefited poor laborers.

INSERT TABLE 5 ABOUT HERE

5.1 Labor intensity *vs*. labor efficiency

The difference in the wage rate reported in table 5 could also be due to efficiency factors. We remind the reader that labor expenditure, W, is given by the product $L^h\lambda(w)$, where L^h is the number of units of labor hired, and $\lambda(w)$ measures labor efficiency. Therefore, by deriving the elasticity coefficient $(dW/W)/(dL^h/L^h)$, we can get a linear parameter estimate from $d(\ln W)/d(\ln L^h)$, and then estimate a relative change in labor efficiency, $d\lambda(w)$. If the computed elasticity is greater than one, then an efficiency factor might be driving up the wage rate.

Consequently, we estimate the predicted elasticity coefficient by computing the regression equation $W_i = \alpha_w + L_i^h\beta_w + u_i^w$ on the observed values, W_i. The regressor L_i^h is a continuous variable that captured the number of units of labor hired (in hours) per month. This variable is transformed into logarithmic form and coded as LGHOURSLABPM. As both labor expenditure, W_i, and units of labor hired, L_i^h, are in log form, we are able predict the *relative change in labor efficiency*.

The results from the regression equation report an elasticity in the order of 1.19 and statistically significant at 1% level (*t*–statistic= 5.73, *p*= 0.00)[xii]. Our findings suggest that enterprising households not only increase labor expenditure as a consequence of higher levels of labor intensity, but also due to efficiency factors. Unfortunately, given data restrictions, we were unable to determine whether wage differences emerged as an indirect effect of program participation or simply because better off households were able to hire relatively more skilled workers. We speculate the former given the proximity of the predicted elasticity to the unity, although more research will be needed to confirm such supposition. In the following section, we examine the impact of microcredit on children schooling.

6. The impact of microcredit on children´s schooling

The examination of the impact of credit on children schooling is particularly relevant in the context of the income-human capital relationship that affects children´s future earnings. Our argument relies on the strong and positive association between children's schooling and *future* levels of labor productivity (see e.g. Spence 1973 and Schultz 1988). On the one hand, if rising levels of labor intensity, as a result of participating in a microcredit program, increase the propensity of child labor from young family members, then long-run patterns of development could be seriously compromised. On the other hand, if access to credit plays the role of an *ex-post* risk-coping mechanism against idiosyncratic income variability and transitory external shocks, then an *indirect* impact on children's schooling could be observed, with long-run effects on labor productivity, and the poverty trap[xiii].

The particular characteristics of the education system in Mexico, where primary and secondary instruction are free of tuition fees, complicated the use of household expenditure on formal education as a variable to fully capture the level of households´ investment in human capital. In fact, the use of such a variable would have only accounted for seasonal expenditure on uniforms, shoes or stationery. For that reason, we decided to concentrate on a qualitative response variable (coded as SCHOOLING) that captures household decisions of whether or not stop sending their children to school. We considered children aged 5 to 17 from the sampled households at the time the survey was conducted. The nature of this variable allows us to predict the *propensity* of children's dropouts by the estimation of a probit model (Goldberger 1964) in the form:

$$c_i^* = X_i\beta + u_i \tag{16}$$

which is based on an underlying response variable c_i^* that takes the values $c = 1$ if $c_i^* > 0$, i.e. if household *i* decides to stop sending their children to school; and $c = 0$ otherwise.

Equation (16) is defined by the probability function

$$\text{Prob}(c_i = 1 | X_i) = \int_{-\infty}^{X_i\beta} \phi(t)dt = \Phi(X_i\beta) \quad (17)$$

where the observed values captured in c follow a binomial distribution with probabilities depending on X_i. In other words, we assume that at least a group of independent variables in X_i explain the decision to stop sending children to school. In order to derive the marginal effects of model (16), we estimate the effect of one unit change in the explanatory variables on the probability of children´s dropouts as follows:

$$ME = \frac{\partial P(c_i = 1)}{\partial X_i} = \frac{\partial \Phi(X_i\beta)}{\partial X_i} \quad (18)$$

where the rates of change are computed in STATA at the means of the independent variables[xiv]. We have included in (16) the same vector of credit markets characteristics, K_i and the impact variable, C_i, just as derived earlier in equation (12) to get:

$$c_i = \alpha_c + X_i\beta_c + K_i\theta_c + C_i\delta + u_i^c \quad (19)$$

where the slope coefficient δ measures the impact of *a relative change in the units of capital borrowed on the propensity of children´s dropouts*. Note that a *negative* sign in δ is expected if *positive* impacts of microcredit are the desirable goal. We have estimated equation (19) with I_i and M_i in substitution of C_i where δ captures, in the case of the former, the impact of *program participation on the school enrolment status*, whereas in the case of the latter, the impact *of one additional year of program participation on the propensity of children's dropouts*. As we expected, the slope coefficient δ reports a *negative* sign in each of the impact variables (see table 6).

INSERT TABLE 6 ABOUT HERE

Other things held constant at the mean, the marginal effects of a one percent increase in the amount of credit borrowed was predicted to *decrease* the probability of children's dropouts by about 0.023 percentage points. Similarly, when equation (19) was computed with I as the impact variable, treatment households reported, on the average, a 25% lower probability of withdrawing their children from school relative to the corresponding control group. Additionally, when equation (19) was computed with M as the impact variable, we find that the marginal effect of one additional year of participation in a microcredit program was predicted to decrease the probability of children's dropouts by about 0.040 percentage points, *ceteris paribus*. This relatively small impact may reflect three different phenomena:

1) The presence of a short-run opportunity cost of school enrolment that increases once children get older and are able to generate income. If by borrowing from a microcredit programme, households manage to increase labor intensity (as reported in section 4), then an increased propensity of employing units of labor from young family members may be observed. In that context, access to credit, in combination with other policies such as cash grants to poor children conditional on school attendance, could substantially reduce negative long-run impacts of credit on human capital.

2) A substitution effect that has been reported by Pitt and Khandker (1998) in the context of Bangladesh. This substitution effect could emerge between parents' and children's time in self-employment activities and group meetings. If by borrowing from a microcredit program women spend several hours in periodical group meetings, then the oldest children's time may be used to substitute the time women's withdraw from childcare or productive activities. In this sense, institutional efforts aimed to reduce the time-intensity of group lending technology could have important long-run impacts on human capital.

3) The effect of idiosyncratic income variability and transitory external shocks. When a household experiencing a sudden destabilizing event chooses to borrow additional money from, say, the local moneylender, this decision may prevent parents withdrawing their children from school in the short-run, although may actually increase the probability of

children's dropouts in the long-run.

An interesting structural property of equation (19) with M as the impact variable is that allows us to estimate the predicted probabilities of children´s dropouts by different groups of households, overtime. To illustrate this, consider the following cases: *Group 1* is formed of women borrowing only from a microcredit program. *Group 2* is formed of women borrowing from a microcredit program and participating in rotating credit and savings associations (ROSCAS). *Group 3* is formed of women borrowing from a microcredit program and other lenders such as savings and credit co-operatives and moneylenders (FORMALCREDIT and MONEYLENDER, respectively). Finally, g*roup 4* is formed of women borrowing from a microcredit program, other lenders and participating in ROSCAS (see table 7).

INSERT TABLE 7 ABOUT HERE

We have computed equation (19) employing the four groups of female borrowers and holding the rest of the variables at the mean. The slope coefficient reports the predicted probabilities of children's dropouts for an *absolute change in the length of program participation*. The results are shown in figure 3. As we expected, the slope coefficient shows a negative sign for each group of female borrowers, reflecting an inverse relationship between the length of program participation and children's dropouts; however, the magnitude of the impact is substantially different between groups, depending on the level of women's indebtedness. For instance, women with one year of program participation and borrowing only from a microcredit program (group 1) report a *decreasing* predicted probability of children's dropouts in the order of $\Pr(y_i = 0.23 | M_i = 1)$ relative to $\Pr(y_i = 0.27 | M_i = 0)$ of the control group, whereas women in the same category but with 5 years of membership reported a much lower probability $\Pr(y_i = 0.10 | M_i = 5)$. We observed a very similar pattern in group 2, where women combined a microcredit with voluntary savings at rotating savings and credit associations.

INSERT FIGURE 3 ABOUT HERE

On the contrary, women borrowing from both a microcredit program *and* other lenders, with no participation in ROSCAS (group 3) have a much higher probability of withdrawing their children from school. We estimate that by borrowing from a moneylender, women increase the probability of children´s dropouts up to 75% *ceteris paribus*, and although this probability falls overtime, the negative impact remains considerable high even after 5 years of program participation, $\Pr(y_i = 0.50 | M_i = 5)$.

In this sense, institutional efforts aimed to design ex-post *protective* risk-coping products such *emergency loans* and *insurance schemes* could have important impacts on human capital. Moreover, ex-ante *preventive* services, additional to voluntary savings schemes, aimed to improve *financial literacy* could reduce the propensity of households falling into a cycle of debt. Although experimentation and analysis will be needed to identify costs and benefits of policies of this kind, it is clear that benefits from financial literacy may go well beyond the expected rate of loan default.

7. Conclusions and policy recommendations

Our study has given important insights on the dynamics involving the relationship between credit and wider impacts on labor and human capital, with important implications for policy and institutional design: poverty targeting, either due to donors conditionality or organizational goals, is a common practice in microcredit to ensure that credit delivery reaches the intended beneficiary. This is done through indirect mechanisms such as upper limits on progressive lending or rigid monitoring devices such as periodical repayment schedules in group meetings that often keep out better off households from borrowing. However, the evidence suggests that poverty targeting may actually diminish important *trickle down* effects through labor markets that could *indirectly* benefit poor laborers. Once enterprising households reach a minimum threshold of income, estimated at a level approximately three times as high as the poverty line derived for urban poverty in Mexico, the marginal propensity to hire units of labor increased significantly. We envisage that income level as a *platform for employment generation*. This platform is particularly important in the context of urban poverty, where farming activities are practically non-existent and labor usually represents the only income source for the *extreme poor*.

In this sense, by simply opening up the upper limits of progressive lending, microcredit programs could significantly increase the probability of achieving wider impacts through labor markets. As Mosley and Rock (2004:481) have pointed out *"this opens up the possibility that […] poverty impact may be maximized by targeting microfinance on the vulnerable non poor, allowing the labor market to assume the brunt of the poverty reduction job".*

The evidence also suggests that the rigidity of monitoring devices such as periodical repayment schedules in group meeting may prevent borrowers to invest more units of labor and consequently, diminish the propensity of labor intensity. The time-intensity of such peer-monitoring devices may also exacerbate the *substitution effect* between parents' and children's time in self-employment activities and group meetings, with adverse impacts on children´s schooling and long-run effects on human capital. In this sense, any possible policy action directed to cut down time in group meetings, through improvements in the prevailing lending technology and practices could have significant wider impacts on human capital. In that course, experimentation should be encouraged, and perhaps facilitated by governmental agencies and other donors, to improve market efficiency and poverty impacts, through a number of possible policy actions that we summarize in table 8.

Expanding access to credit (and other financial services) is, beyond all doubt, critical for the poor. However, design factors can constrain the magnitude of the expected impacts. In that context, we hope that our findings will serve as *stimuli* to the microcredit industry to explore other possible ways to improve practice and increase impact. In that effort, both institutions and households win, and the orthodox hypothesis of divisibility between equity and efficiency simply collapses.

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References

Amemiya T. (1984) Tobit models: a survey, in: Journal of Econometrics, Vol. 84 pp. 3-61

Babbie, E. (1990) Survey research methods. Belmont, CA: Wadsworth

Bardhan, P. and Rudra, A. (1986) Labour mobility and the boundaries of the village moral economy in: Journal of peasant Studies, 13

Campbell, D. and Stanley, J. (1966) Experimental and Quasi-experimental designs for research, in: N.L. Gage (Ed), Handbook of research on teaching, pp. 1-76. Chicago: Rand McNally

Dasgupta, P. and Ray, D. (1986) Inequality as a determinant of malnutrition and Unemployment: theory, in: Economic Journal, 96

Dasgupta, P (1993) An enquiry into wellbeing and destitution. Oxford: Clarendon Press

Fink, A. and Kosecoff, J. (1985) How to conduct surveys: A step-by-step guide. Beverly Hills, CA: Sage Publications

Foster A. and Rosenzweig, M. (1996) Comparative Advantage, information and the allocation of workers to tasks: Evidence from an agricultural labor market, in: Review of Economic Studies, 63

Goldberger A. (1964) Econometric Theory. John Walley & Sons, New York

Greene W. (2003) Econometric Analysis. Prentice Hall, Fifth edition.

Halvorsen R. and Palmquist R. (1980). The interpretation of dummy variables in semilogarithmic equations, in: American Economic Review, Vol. 70 No. 3, pp. 474-5

Hausman J. (1978) Specification test in Econometrics, in Econometrica, 46, pp 1251-1271

Heckman J. (1979) Sample selection bias as a specification error, in Econometrica, Vol. 46, pp, 153-61

Klein L (1961) An introduction to Econometrics, Prentice Hall, Englewood Cliffs, N.J.

Leibbenstein, H. (1957) Economic backwardness and economic growth. New York: John Wiley

Ljungqvist, L. (1993) Economic Underdevelopment: the case of a missing market for Human Capital, in Journal of Development Economics, 40

Maddala G. (1999) Limited dependent and qualitative variables in Econometrics. Econometric Society Monographs, Cambridge University Press

Mazumdar, D. (1959) The marginal productivity theory of wages and disguised unemployment, in: Review of Economic Studies, 26

McDonald J. and Moffitt (1980) The use of Tobit analysis, in: Review of Economics and Statistics, Vol. 62, pp. 318-321

Mosley and Rock (2004) Microfinance, labour markets and poverty in Africa: A case of six Institutions, in: Journal of International Development, 16

Schultz T. (1988) Education investments and returns in H. Chenery and T.N. Srinivasan (eds), Handbook of Development Economics, i. Amsterdam: North-Holland

Secretaria de Desarrollo Social (Sedesol) (2002) Medición de la Pobreza. Variantes metodológicas y estimación preliminar, Comité Técnico para la Medición de la Pobreza. Serie: documentos de investigación, julio.

Spence, A. (1973) Job market signalling in Quarterly Journal of Economics, 87

Pitt, M. and Khandker, S. (1998) Household and intra-household impact of the Grameen Bank and similar targeted credit programs in Bangladesh, in: Journal of Political Economy, Vol. 106, 558-596

Rothbarth, E. (1943). 'Note on a method of determining equivalent income for families of different composition', in C. Madge (ed) War-time Pattern of Saving and Spending, Cambridge University Press, Cambridge.

Tobin J. (1958) Estimation of relationships for limited dependent variables, in: Econometrica, Vol. 26, pp. 24-36

Wooldridge J. (2002) Econometric analysis of cross section and panel data. London: MIT Press.

Notes

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[i] Contact at: University of Sheffield. 9 Mappin Street, S1 4DT Sheffield, United Kingdom. Tel: +44 114 222 3343, Email: m.nino@sheffield.ac.uk

[ii] This *maximum* is the upper limit of the cost of buying an efficiency unit of labor that an enterprising household is willing to pay.

[iii] For more details about the instruments of data collection, contact the authors at m.nino@sheffield.ac.uk

[iv] See Wooldridge (2002), Greene (2003) and Maddala (1999) for a detailed discussion on the properties of the identifying instrument.

[v] Since we have a data-censoring case demanding the variable C_i^* to follow a homoskedastic normal distribution, we use a logarithmic transformation in our estimation strategy to make this assumption more reasonable.

[vi] For further details on the derivation of the conditional mean functions, see Greene (2003).

[vii] McDonald and Moffitt (1980) have decomposed equation (7.21 into two parts to obtain the effects of a change in X_i on the conditional mean of C_i, and on the probability that the observation will fall in the part of the distribution where $C_i > 0$.

[viii] In fact, we observed that mean value for this time-dimensional variable was 22 minutes for an outward journey.

[ix] We adopted Lawrence Klein's rule of thumb (1961), to test DISTANCE for potential problems of collinearity. We did not find evidence of collinearity.

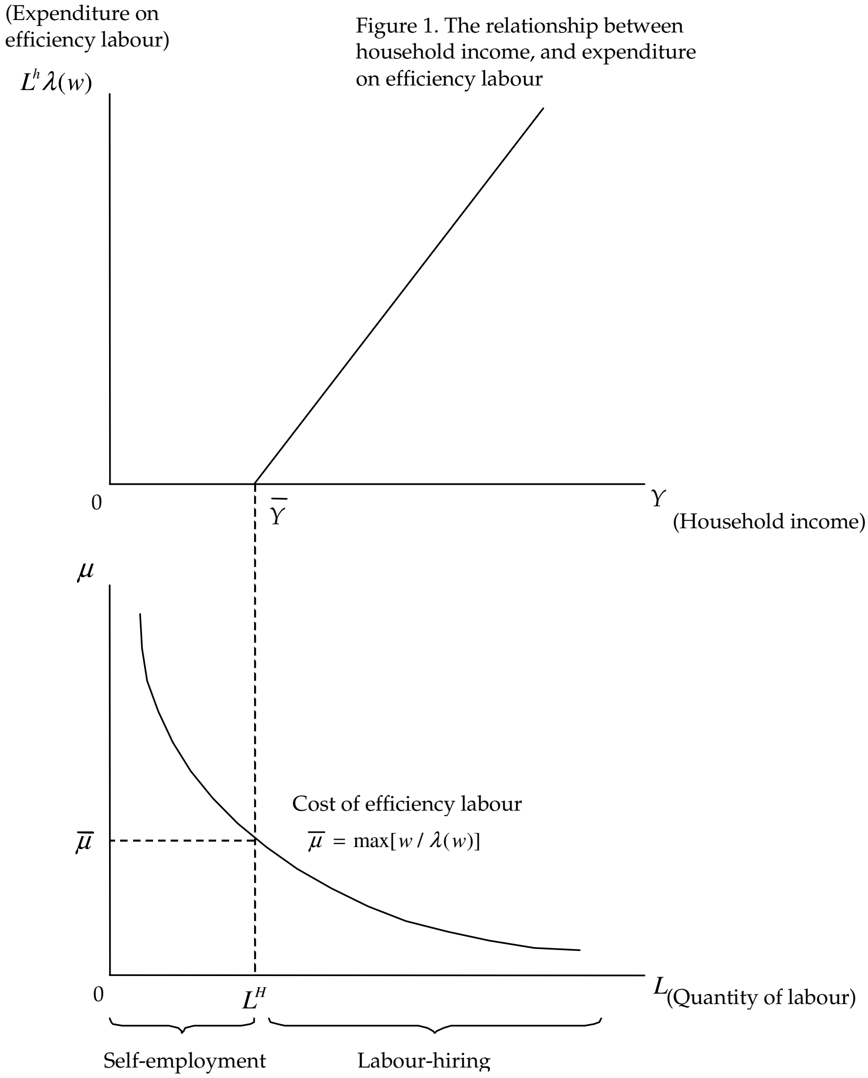
[x] Since we cannot observe λ, we assume that this factor is captured by the wage rate w.

[xi] The poverty line at household level has been set up at 6570 pesos per month, which is the product of the *capability-based* poverty line at 1507.5 per month multiplied by household size using the equivalence factors proposed by Rothbarth (1943).

[xii] The statistics of the regression equations are: $F(1, 20) = 32.81$, $p = 0.00$; $R^2 = 0.52$

[xiii] A poverty trap emerges under situations where, on the one hand, wealthy households can afford to invest in human capital, e.g. in education, health and nutrition, and this enables them to increase their future productivity and wealth. On the other hand, poor households cannot afford to invest in human capital and as a consequence, earn low income and remain in poverty. The relationship between imperfect credit markets and the poverty trap has been analyzed by Ljungqvist (1993).

[xiv] For a discussion of the derivation of the marginal effects for a probit equation see Greene (2003), Maddala (1999) or Wooldridge (2002).



Source: Adapted from Dasgupta and Ray (1986)

Table 1. Characteristics of the case-study microcredit programmes
Information corresponding to 2004

Institutional	**FINCOMUN**	**CAME**	**PROMUJER**
Type of organisation	Credit Union	Non-Governmental Organisation	Non-Governmental Organisation
Year of establishment	1994	1991	2001
Founders	Juan Diego Foundation, a catholic group	Foundation for Community Assistance, belonging to the Archdiocese of Mexico	Pro-Mujer International
Area of influence	San Miguel Teotongo, and other municipalities in the metropolitan area of Mexico City	The Chalco Valley and a few other municipalities of the metropolitan area of Mexico City	Tula City and the surrounding areas in the state of Hidalgo
No of branches	27	5	21
Personnel	339	580	45
Lending methodology	Individual lending	Credit-only village-banking	Credit-plus village-banking
Repayment schedules	16 to 24 weekly instalments at Fincomun officers or HSBC branches	16 weekly instalments in compulsory group meetings.	12 to 24 weekly or fortnightly instalments in compulsory group meetings
Interest rate (per annum)	72%	60%	72%
Savings as % of loan	10	10-12	10-12
Physical collateral	Yes	No	No
Guarantees	Yes, two guarantees	Yes, through joint liability	Yes, through joint liability
Other services	Voluntary savings products and certificates of deposits	Life Insurance to cover loan balance. Extra-loans from the internal revolving fund	Training in financial literacy, business development and health care
Borrowers (000)	25.8	40	11.8
Women borrowers (%)	60	80	100
Gross loan portfolio (000 MEX$)	169,725	58,000	13,739
Average outstanding loan (000 MEX$)	6.6	1.5	2.1
Loan loss reserve ratio (%)	2.7	1.8	2.9

Table 2. Testing the identifying instrument DISTANCE for the Heckit and Tobit selection equation
Dependent variable in equation (12): logarithm of the maximum amount of credit borrowed (LGMAXCREDIT)
Dependent variable in equation (2): The Heckman procedure transforms LGMAXCREDIT into a dummy variable for treatment group = 1 if $I > 0$
Dependent variable in equation (13): Logarithm of units of labour invested during the last month (LGAGHOURSPM)

Explanatory Variables	1S-Heckit (Eq. 2)	1S-Tobit (Eq. 12)	2SLS (Eq. 13)
DISTANCE	**0.028**	**0.095**	**-0.004**
	(5.08)*	**(3.69)***	**(1.48)**
AVEDU	-0.053	-0.215	-0.041
	(1.44)	(1.26)	(2.37)**
HOWNER	0.252	1.548	0.196
	(0.99)	(1.25)	(1.45)
HESTATE	0.449	2.153	-0.004
	(1.58)	(1.50)	(0.03)
TIMEBUS	0.001	0.014	0.023
	(0.06)	(0.14)	(2.25)**
WWORKER	-0.157	-0.772	-0.423
	(0.95)	(0.91)	(3.77)***
DEPENDRATIO	0.200	0.961	0.783
	(0.35)	(0.34)	(2.52)**
AGE	-0.015	-0.064	-0.016
	(1.11)	(1.00)	(2.12)**
WOMAN	0.185	0.831	-0.278
	(0.69)	(0.62)	(2.22)**
MARITAL	-0.093	-0.466	-0.037
	(0.33)	(0.35)	(0.24)
ROSCAS	0.155	0.629	0.061
	(0.67)	(0.56)	(0.48)
FORMALCREDIT	-0.558	-2.506	-0.017
	(1.30)	(0.98)	(0.09)
MONEYLENDER	-1.101	-5.879	-0.032
	(2.87)***	(2.69)***	(0.19)
CONSTANT	-0.072	2.159	6.427
	(0.08)	(0.51)	(16.07)***
Observations	148	148	137
Pseudo R^2 / R^2	0.1553	0.0394	0.25
Wald χ^2 / LR χ^2 / F stat	37.97	27.93	4.21
Prob > χ^2 / Prob > F	0.0003	0.0093	0.0000

Robust z-statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3. The impact of credit on labour intensity
Dependent variable: Logarithm of units of labour invested during the last month (LGAGHOURSPM)
Impact variables: Logarithm of the maximum amount of credit (LGMAXCREDIT), and Length of membership in years (MEMBERSHIP)

	Heckit	OLS	2S-Tobit	OLS	OLS
AVEDU	-.066	-0.034	-0.031	-0.033	-0.035
	(2.46)**	(1.95)*	(1.82)*	(1.96)*	(2.17)**
HOWNER	.290	0.163	0.139	0.151	0.096
	(1.35)	(1.22)	(1.04)	(1.13)	(0.71)
HESTATE	-.132	0.012	0.004	0.014	-0.022
	(0.59)	(0.08)	(0.03)	(0.09)	(0.14)
TIMEBUS	.035	0.024	0.023	0.024	0.023
	(2.06)**	(2.32)**	(2.24)**	(2.31)**	(2.25)**
WWORKER	-.359	-0.405	-0.396	-0.404	-0.397
	(2.37)**	(3.71)***	(3.60)***	(3.73)***	(3.69)***
DEPENDRATIO	.874	0.827	0.816	0.830	0.821
	(1.94)*	(2.70)***	(2.71)***	(2.73)***	(2.84)***
AGE	-.012	-0.014	-0.013	-0.014	-0.017
	(1.27)	(1.76)*	(1.66)*	(1.74)*	(2.18)**
WOMAN	-.125	-0.281	-0.269	-0.271	-0.311
	(0.57)	(2.31)**	(2.20)**	(2.23)**	(2.51)**
MARITAL	.024	0.011	0.027	0.015	-0.017
	(0.12)	(0.07)	(0.18)	(0.10)	(0.11)
ROSCAS	.135	0.035	0.034	0.035	0.022
	(0.76)	(0.28)	(0.27)	(0.28)	(0.18)
FORMALCREDIT	.269	-0.031	-0.015	-0.025	-0.022
	(0.64)	(0.17)	(0.08)	(0.13)	(0.11)
MONEYLENDER	-.363	0.062	0.106	0.062	0.032
	(0.83)	(0.37)	(0.59)	(0.37)	(0.20)
LGMAXCREDIT†	0.143	**0.233**			
	(1.47)	(1.86)*			
LGMAXCREDIT			**0.014**	0.029	
			(0.63)	(2.11)**	
MEMBERSHIP					**0.092**
					(2.90)***
MILLS	.639				
	(1.60)				
RESID			0.017		
			(0.83)		
CONSTANT	4.47	5.974	5.917	5.944	6.212
	(4.16)***	(14.34)***	(14.18)***	(14.23)***	(16.65)***
Observations	137	137	137	137	137
Pseudo R^2 / R^2		0.26	0.27	0.26	0.28
Wald χ^2 / LR χ^2 / F stat	41.92		4.08	4.50	4.97
Prob > χ^2 / Prob > F	0.0183		0.0000	0.0000	0.0000

Robust z- and t -statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%
† LGMAXCREDIT has been transformed into a dummy variable for treatment group = 1 if $I > 0$ to follow the Heckman procedure.

Table 4. Determinants of labour expenditure

Dependent variable: Logarithm of household expenditure on labour (LGWAGEXP)

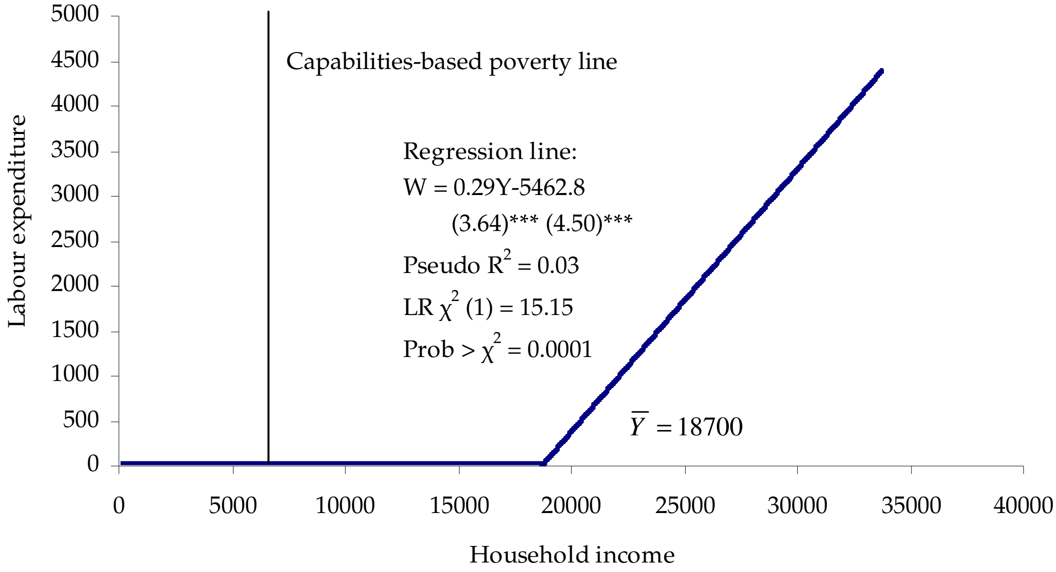
LGHINCOME	7.777 (2.80)***			
LGMAXCREDIT		0.225 (0.68)		
MEMBERSHIP			0.300 (0.40)	
LGMAXCREDIT †				1.122 (0.37)
Observations	148	148	148	148
Pseudo R2	0.039	0.019	0.006	0.005
LR chi2	9.84	0.47	0.16	0.14
Prob > chi2	0.0017	0.4929	0.6884	0.7107

Absolute value of t statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

† LGMAXCREDIT is transformed into a dummy variable = 1 for treatment households

Figure 2. The relationship between household income and labour expenditure (Figures in pesos of 2004)



Absolute value of t statistics in parentheses. *** significant at 1%

Table 5. Relationship between programme participation and labour

	Treatment	Control
Self-employed per household (average)	1.60	1.35
Self-employment as % of income sources	75.39	69.37
Labour-hirers as proportion of total borrowers (%)	15.56	13.79
Labourers per household-hirer (average)	1.5	1.3
Average hours worked per week	34+++	19.72
Wage paid as % of the food-based poverty line (784.5 pesos per month)	240.39	123.70
Wage paid as % of the capability-based poverty line (1507.5 pesos per month)	125.10	64.37
Wage paid as % of the asset-based poverty line (1881 pesos per month)	100.26	51.59

The statistically significant association in the cross-tabulations are indicated by the Chi-square values for the cell as a whole at 0.001 (+); 0.01 (++); 0.05 (+++); and 0.1 (++++) levels of significance.

Source. Authors´ sample survey 2004

Table 6 Probit estimation: The impact of programme participation on children schooling
Dependent variable: dummy variable = 1 if household *i* has stopped sending children to school (SCHOOLING)

	Equation (19) with C_i as explanatory variable a/		Equation (19) with I_i as explanatory variable b/		Equation (19) with M_i as explanatory variable c/	
	Coef	$\frac{\partial\Phi}{\partial \mathbf{X}}$	Coef	$\frac{\partial\Phi}{\partial \mathbf{X}}$	Coef	$\frac{\partial\Phi}{\partial \mathbf{X}}$
AVEDU	-0.066	-0.019	-0.068	-0.020	-0.055	-0.016
	(1.64)	(1.64)	(1.68)*	(1.68)*	(1.39)	(1.39)
HOWNER	-0.317	-0.096	-0.336	-0.101	-0.269	-0.082
	(1.14)	(1.14)	(1.21)	(1.21)	(0.97)	(0.97)
HESTATE	0.279	0.075	0.286	0.077	0.276	0.076
	(0.92)	(0.92)	(0.93)	(0.93)	(0.90)	(0.90)
TIMEBUS	0.026	0.008	0.026	0.008	0.026	0.008
	(1.39)	(1.39)	(1.41)	(1.41)	(1.29)	(1.29)
WWORKER	0.418	0.121	0.420	0.121	0.445	0.130
	(2.42)**	(2.42)**	(2.42)**	(2.42)**	(2.55)**	(2.55)**
DEPENDRATIO	0.312	0.090	0.320	0.092	0.244	0.071
	(0.49)	(0.49)	(0.50)	(0.50)	(0.40)	(0.40)
AGE	0.024	0.007	0.024	0.007	0.029	0.009
	(1.70)*	(1.70)*	(1.70)*	(1.70)*	(1.99)**	(1.99)**
WOMAN	0.301	0.082	0.325	0.088	0.327	0.090
	(0.98)	(0.98)	(1.05)	(1.05)	(1.12)	(1.12)
MARITAL	-1.169	-0.395	-1.186	-0.400	-1.065	-0.360
	(4.04)***	(4.04)***	(4.07)***	(4.07)***	(3.79)***	(3.79)***
ROSCAS	0.032	0.009	0.050	0.014	0.039	0.011
	(0.12)	(0.12)	(0.19)	(0.19)	(0.15)	(0.15)
FORMALCREDIT	0.237	0.074	0.238	0.074	0.211	0.066
	(0.57)	(0.57)	(0.57)	(0.57)	(0.51)	(0.51)
MONEYLENDER	0.930	0.330	0.887	0.312	1.075	0.387
	(2.45)**	(2.45)**	(2.35)**	(2.35)**	(2.90)***	(2.90)***
LGMAXCREDIT	**-0.082**	**-0.024**	**-0.824**	**-0.251**		
	(2.74)* **	**(2.74)*** **	**(3.05)*** **	**(3.05)*** **		
MEMBERSHIP					-0.135	-0.040
					(1.88)*	(1.88)*
CONSTANT	-0.883		-0.823		-1.506	
	(0.88)		(0.82)		(1.55)	
Observations	148	148	148	148	148	148
LR Chi-squared	39.31	39.31	40.37	40.37	37.28	37.28
Pseudo R-squared	0.28	0.28	0.29	0.29	0.26	0.26
Log likelihood	-62.23	-62.23	-61.46	-61.46	-64.20	-64.20

Robust z statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%
a / C_i: logarithm of the maximum amount of credit borrowed (LGMAXCREDIT)
b/ I_i: LGMAXCREDIT is transformed into a dummy variable = 1 for treatment households
c/ M_i : number of years of programme participation (MEMBERSHIP)

Table 7: Female borrowers by different source of funding

	Control group	Treatment group
Group 1	Savings at home, and occasional loans from relatives, friends or suppliers, i.e. $MEMBERSHIP = 0$, $ROSCAS_i = 0$, $FORMALCREDIT_i = 0$ and $MONEYLENDER_i = 0$	Only loans from MFI i.e. $MEMBERSHIP_i > 0$, $ROSCAS_i = 0$, $FORMALCREDIT_i = 0$ and $MONEYLENDER_i = 0$
Group 2	Savings in rotating savings and credit associations and occasional loans from relatives, friends and suppliers $MEMBERSHIP = 0$, $ROSCAS_i = 1$, $FORMALCREDIT_i = 0$ and $MONEYLENDER_i = 0$	Loans from the MFI and savings in rotating savings and credit associations, i.e. $MEMBERSHIP_i > 0$, $ROSCAS_i = 1$ $FORMALCREDIT_i = 0$ and $MONEYLENDER_i = 0$
Group 3	Loans from institutional lenders and moneylenders. Probably savings at home, i.e. $MEMBERSHIP = 0$, $ROSCAS_i = 0$, $FORMALCREDIT_i = 1$ and $MONEYLENDER_i = 1$	Loans from the MFI, and institutional lenders and moneylenders, i.e. $MEMBERSHIP_i > 0$, $ROSCAS_i = 0$, $FORMALCREDIT_i = 1$ and $MONEYLENDER_i = 1$
Group 4	Loans from institutional lenders and moneylenders and saving in rotating savings and credit associations, i.e. $MEMBERSHIP = 0$, $ROSCAS_i = 1$, $FORMALCREDIT_i = 1$ and $MONEYLENDER_i = 1$	Loans from the MFI, and institutional lenders and moneylenders, and savings in rotating savings and credit associations, i.e. $MEMBERSHIP_i > 0$, $ROSCAS_i = 1$ $FORMALCREDIT_i = 1$ and $MONEYLENDER_i = 1$

Figure 3. Predicted probabilities of children's dropouts per length of programme participation

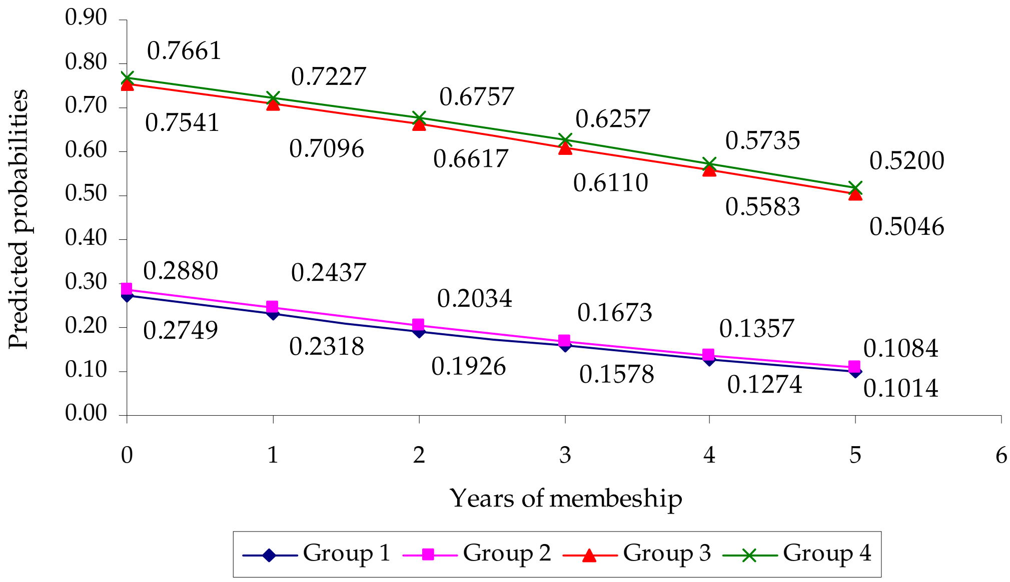


Table 8: Summary of findings and policy recommendations

Impacts on	Findings	Policy recommendations for experimentation	Expected benefits
Labour intensity	Employing the logarithm of the maximum amount of credit, C, as impact variable: small elasticity of labour intensity with respect to credit. A 1% increase in credit is predicted to increase in 0.029% the units of labour invested. Employing a dummy variable for treatment households = 1, if $I > 0$, as impact variable: the median of units of labour invested by treatment households was estimated to about 26% higher than that of control groups.	Introduction of more efficient lending technology and practices to cut down peer-monitoring devices that characterise group lending.	Increasing propensity of labour intensity, children´s schooling and long-term impacts on human capital.
	Employing the length of membership, M, as impact variable: the units of labour invested were predicted to increase at an annual rate of 9.6% after joining a microcredit programme, from 499 to 547 hours per month.	Combination of credit with cash grants for children from the poorest households, conditional on school attendance.	Reduce the propensity of child labour emerging from a short-run opportunity cost of school enrolment when the propensity of labour intensity increases.
Labour hiring	Large elasticity of labour expenditure with respect to household income. A 1% increase in household income is predicted to give rise to a 7.8% in labour expenditure. The large elasticity is explained by low level of initial wages relative to household income. We find that only households well above the poverty line were able to hire labourers. Significant association between treatment and control groups in relation to wages paid to labourers.	Removal of credit targeting that could be facilitated by the abolition of conditionality from governmental agencies and donors, and the elimination of upper limits of progressive lending that could be linked to the introduction of individual lending products for "graduated" borrowers.	Trickle down effects through labour markets that could indirectly benefit poor labourers. Improvements in client retention, institutional self-sufficiency and market efficiency.
Labour efficiency	Relative change in labour efficiency in the order of 1.19, reflecting efficiency factors driving up labour expenditure.		
Children´s schooling	Employing the logarithm of the maximum amount of credit, C, as impact variable: a significant although small decreasing probability of children´s dropouts by 0.02% relative to a 1% increase in the amount of credit borrowed. Employing a dummy variable for treatment households = 1, if $I > 0$, as impact variable: a significant and 25% lower probability of treatment households withdrawing their children from school vis-à-vis the corresponding control group.	Introduction of ex-post protective risk-coping products such as emergency loans insurance schemes.	Improving poor household's risk-coping mechanisms to cope with idiosyncratic income variability and transitory external shocks, with important effects on human capital and the expected rate of loan default.
	Employing the length of membership, M, as impact variable: a decreasing predicted probability of children´s dropouts of 0.04% per additional year of programme participation. Important differences in the propensity of children´s dropouts depending in the magnitude of women's indebtedness.	Introduction of ex-ante preventive products, additional to voluntary savings schemes, aimed to improve financial literacy amongst programme participants.	Improvements in financial education, potential long-terms effects on human capital and reductions in the expected rate of loan default.

Table 9. List of variables

Impact variables	Definition	Obs	Mean	S.D.	Min	Max
LGMAXCREDIT	Logarithm of the maximum amount of credit borrowed in the last credit cycle	148	5.475	4.466	0	10.621
LGMAXCREDIT†	If household has been treated = 1	148	0.608	0.490	0	1
MEMBERSHIP	Years of membership	148	1.704	1.944	0	8
Dependent variables						
LGAGHOURSPM	Logarithm of hours of labour invested in production, including labour hiring	148	5.169	1.653	0	7.352
LGWAGEXP	Logarithm of household expenditure on labour-hiring per month	148	1.107	2.672	0	8.556
SCHOOLING	If household has stop sending children to school = 1	148	0.270	0.446	0	1
LGHINCOME	Logarithm of household income per month	148	8.697	0.537	7.244	10.254
Independent variables						
Contained in X_i						
AVEDU	Years of education	148	7.047	3.777	0	17
HOWNER	If household owns residence = 1	148	0.682	0.467	0	1
HESTATE	If house is still in construction = 1	148	0.791	0.408	0	1
TIMEBUS	Years in business	148	5.162	5.746	0	30
WWORKER	Number of household members with a waged job	148	0.547	0.703	0	3
DEPENDRATIO	Dependency ratio (number of children, students and old members / household size)	148	0.498	0.222	0.125	1
AGE	Age of borrower	148	42.189	10.846	19	74
WOMAN	If borrower is woman = 1	148	0.730	0.446	0	1
MARITAL	If borrower is in a relationship = 1	148	0.757	0.430	0	1
Contained in L_i						
ROSCAS	If borrower participates in rotating savings and credit association = 1	148	0.453	0.499	0	1
FORMALCREDIT	If borrower have received loans from institutional lenders = 1	148	0.054	0.227	0	1
MONEYLENDER	If borrower have received loans from moneylenders	148	0.095	0.294	0	1
Instrumental variable						
DISTANCE	Distance from branch to place of residence or business (in minutes)	148	32.365	21.716	10	100