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Microcredit, Labor, and Poverty Impacts in Urban Mexico

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Abstract

Improved household accessibility to credit is a significant determinant of intra-household allocation of labor resources with important implications for productivity, income, and poverty status. However, credit accessibility could also have wider impacts on poverty if it leads to new hires outside the household. This paper contributes to the existing literature on microcredit in two important ways. First, it investigates the routes through which microcredit reaches those in poverty outside the household. We test whether by lending to the vulnerable non-poor microcredit can indirectly benefit poor laborers through increased employment. Second, we conduct the study in the context of urban poverty Mexico. This is relevant when considering that labor often represents the only source of livelihoods to the extreme urban poor. Our findings point to significant trickle-down effects of microcredit that benefit poor laborers; however, these effects are only observed after loan-supported enterprising households achieve earnings well above the poverty line.

1. Introduction

It is now widely understood that credit markets ration loans to those in poverty. In developing countries in particular, credit markets suffer from informational asymmetries, which raise the need for collateral and therefore exclude those with low capital endowments. Caskey et al. (2006), for instance, report that about two thirds of low-income households living in the Metropolitan area of Mexico City were "unbanked", and among those "anked", only a small percentage had access to credit. Credit rationing implies that households in poverty are not able to allocate their labor resources optimally. In this context, the improved availability of credit to these groups should lead to a re-allocation of their labor resources, with implications for their productivity, income, and poverty status.

The improved access to credit could in addition have a wider impact on poverty if it leads to new hires among fully or partially unemployed workers outside the loan-supported household. The existing literature on microcredit, which focuses mostly on rural areas, suggests that this wider impact on poverty through new hires is likely to be small at best, partly because of labor-market rigidities. Khandker (1998) for instance, finds in the context of rural Bangladesh, an increase in self-employment as result of household participation in microcredit programmes, although most income-generating activities rarely involved workers outside the household. Dasgupta and Ray (1986) suggest that this is partly because at low levels of income, enterprising

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households can only afford to employ unskilled and malnourished laborers with very low productivity. Informational constraints regarding the productivity of potential hires may also prevent enterprising households from hiring labor, with self-employment perceived as the less risky choice. However, if a household reaches the upper limit of its available labor supply, then new hires can emerge as a strong alternative for production, with implications for the poverty status of poor laborers. Mosley and Rock (2004) report significant impacts on poor laborers employed by loan-supported enterprising households, members of microcredit programs operating in Africa. The extent to which microcredit leads to increased employment among the extreme urban poor is crucial, especially as labor often represents the only source of livelihoods for this group.

This paper explores this issue employing quasi-experimental data collected from three microcredit programs operating in Mexico. The study contributes to the literature on microcredit impacts in two important respects. First, the study focuses on the spatial dimension of urban poverty. This is critical when considering that, unlike in rural markets; labor often represents the only source of earnings for the extreme poor. We exploit the spatial dimension to deal with endogeneity problems in the econometric estimation procedure presented below. Second, we investigate the routes through which microcredit reaches those in extreme poverty outside the household. We test whether, by lending to non-poor enterprising households, microcredit organizations can indirectly benefit poor laborers through increased employment.

2. Microcredit and Labor Supply

As a starting point for the examination of the relationship between microcredit and labor supply, it is useful to consider, for expositional purposes, the hypothetical case of an enterprising household engaging in an income generating activity to produce 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 production technology. As pointed out by Pitt and Khandker (1996), it is very unlikely that at the bottom-end of the income distribution technology changes, at least in the short-term, so α is assumed to be constant.

In the production of y, the enterprising household is assumed to supply the amount of labor L^h, constrained to the number of household members of working-age, i. This is defined as $L^H = \underset{i,h}{\mathrm{Max}}\, N[i(h)]$, implying that under self-employment, labor supply equals the maximum number of hours worked, h, contributed by household members of working-age. If production technology does not change, an injection of capital from microcredit will increase production through household-level labor supply up to L^h, the point at which the allocation of labor resources is maximized. Through this mechanism, microcredit is reported to have a positive impacts on self-employment (Khandker, 1998; McKernan, 2002). However, if more labor is required for production, then hiring laborers outside the household may become a sensible choice. New hires are not only a function of household earnings from production but also of the cost of hiring efficient labor. Leibenstein (1957), Mazumdar (1959), and Dasgupta (1993) have pointed out that labor efficiency is conditional upon factors such as nutritional status, individual abilities, skills and efforts that determine labor productivity. Dasgupta and Ray (1986) have also shown that at low levels of household earnings, non-poor enterprising households that are considering employing laborers as a result of having reached their upper limit of labor supply could find that they can only afford to employ workers with very low productivity. Informational asymmetries can also constrain the demand for labor in poor areas. Bardhan and Rudra (1986) and Foster and Rosenzweig (1996) point out that households may perceive it too risky to employ workers of varying productivity because they do not have enough information about their skills, behavior, or moral integrity, and for that reason they may simply choose to self-employ and produce at sub-optimal levels.

Since our interest is not only to assess the effects of microcredit on self-employment, but also on labor hiring, i.e. the indirect routes through which microcredit impact poor laborers hired by loan-supported households, we derive a cost function for efficient units of hired labor, $\mu = w/\lambda(w)$, that is conditional upon the market wage rate per hour work, w, and unobservable factors that are related to productivity and informational constraints that determine labor efficiency, λ. In the context of fragmented labor markets, these productivity and informational constraints are expected to exacerbate the relative cost of efficient labor, μ, and as a result, new hires will be considered as an alternative for production only if enterprising households reach a minimum threshold of earnings, $\bar{Y}$, the level at which they can afford to pay for this cost.

New hires are observed in the form of household expenditure on labor hiring, denoted here by W, which is the product of units of efficiency labor hired (L^h) and the wage rate, defined by efficiency factors, i.e. $W = L^h\lambda(w)$. This function is similar to that in Dasgupta and Ray (1986); however, in our case the cost function takes a maximum value $\bar{\mu}$ and a lower threshold that is censored at zero for households that self-employ, $\bar{\mu} = \max[w/\lambda(w), 0]$. This implies that at low levels of earnings, no household will hire laborers as they face high costs of buying efficiency units of labor and they remain relying on their own labor resources for production. After the enterprising household reaches a minimum level of earnings, they begin to consider employing workers with a minimum level of skills and abilities required for production. So, if $\bar{\mu}$ is affordable, household expenditure on labor-hiring becomes positive and the employment function becomes $L = L^H + L^h$. The higher the level of household earnings, the lower the relative cost of buying additional units of labor efficiency μ, and the higher the probability of observing new hires outside the family. Credit accessibility can play a crucial role in that process. If households borrowing from microcredit organizations are able to increase their earnings beyond $\bar{Y}$, the likelihood of indirect poverty impacts, through labor markets, becomes promising.

3. Research Design

The study involved a quasi-experiment, in which two groups of households were sampled: treatment and control. A problem that emerges from quasi-experimental research designs is that the two groups of households may differ in important ways that influence the decision of borrowing. In other words, there might be unobservable factors related to individual efforts, abilities, preferences, and attitudes towards risk that may affect the selection process and thus the outcomes of interest. We refer to this problem as a demand-related bias, or simply as self-selection. A fundamental assumption here is that participation in a microcredit program is always voluntary. Another potential selection problem could also emerge from the implicit nature of fragmented credit markets. Even if we observe a group of households 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 who, for instance, live outside the market radius where the microcredit program operates. We refer to this problem as a supply-related bias. Thus, the selection process is defined by two factors: one related to household's decision to participate in a microcredit program, and another associated with the decision of lenders (or group members) to accept the applicant.

In the end, we were able to specify the distribution of households that had self-selected to participate in a credit program, and had been accepted by the lender or group members, but only with a time–variance difference that accounts for the length of membership. As a result, those households who had self-selected to participate in a credit program and had been acceptedby the lender, and therefore were actively borrowing from the credit program were eligible to be sampled as members of the treatment group. Similarly, those households who had self-selected to participate in the microcredit program and had been accepted by the lender, but had just received the first loan by the time the study was conducted, were eligible to be sampled as members of the control group. This sampling strategy helped us to control for selection bias.[1]

In addition, we followed geographical and temporal identification criteria. The geographical criterion consisted of operationalizing the quasi-experiment among households living in the same municipality, in areas with a degree of socio-economic homogeneity. By following this procedure, it was possible to hold constant factors such as infrastructure, local prices, and wages that could have otherwise exacerbated the endogeneity problems. A high population density in urban areas made it possible to adopt this approach. The temporal criterion consisted of selecting market areas within the municipalities where the microcredit organizations had achieved a certain level of penetration and where the effects of microcredit could more likely be observed. Having access to institutional information was crucial to achieve this purpose.

The sampling strategy was implemented using a multistage cluster procedure. First, we had access to a list of program participants (both treatment and control) from three case-study organizations that lived in the selected areas. Participants with loans in arrears were also included in the sample. In the second stage, both treatment and control groups were selected at random. In the end, 148 households participated in the study: 55 households were members of Community Financial Services (Fincomun) and lived in San Miguel Teotongo, a neighbourhood located to the eastern periphery of Mexico City; 46 households were members of the Centre for the Assistance of the Micro-entrepreneur (CAME) and lived in the Chalco Valley, located to the eastern periphery of the Metropolitan area of Mexico City; and 47 households were members of Programs for Women (Promujer), and lived in Tula City.We have thus three market locations, one for each case microcredit programme.[2]

It is important to point out that unlike CAME and Promujer, which employ group lending methodologies, Fincomun mainly relies on individual lending, and demands as a result, physical (rather than social) collateral as enforcement mechanism. The inclusion of Fincomun in the impact study allowed us to evaluate potential differences between group lending and individual lending technology regarding credit impacts on labor supply.

4. The Econometric Model

We begin the discussion by considering the following model:

$$C_i = \alpha_C + X_i \beta_C + Z_i \gamma + u_i^C \tag{1}$$

$$L_i = \alpha_L + X_i \beta_L + C_i \delta + u_i^L \tag{2}$$

where C_t measures the maximum amount of credit borrowed by household i, which is exogenously determined by the lender who defines thatmaximum threshold according to the level of program participation. Note that both treatment and control groups are program participants, differing only by the length of membership. Treatment households with say five years of membership are expected to demand (and be granted), larger credits than that of the control group. This is in part due to the effects of progressive lending, an incentive device extensively used in microcredit to increase the probability of loan repayment. L_i measures the number of units of labor efficiency invested in production, including labor-hiring, whereas X_i is a vector of household characteristics that contains the following factors: (1) the education of household head, used as a proxy of human capital endowments; (2) the dependency ratio, used as a measure of intra-household composition that captures the liquidity requirements for consumption expenditure; (3) the number of years the household has been engaged in income-generating activities, which is used to measure the level of production specialization; (4) housing ownership, used as a measure of physical capital endowments in the urban context, and (5) a dummy variable reflecting whether the borrower is woman (see Table 1).

Z_i is an observable variable distinct from those in X_i that affects the demand for credit but not L_i, and which plays the role of the identifying instrument. The rationale behind including Z_i in equation (1) relies on the fact that although we were able to control for self-selectivity through the research design itself, we could still encounter endogeneity problems if the explanatory variable C_i in equation (2) is correlated with unobservable factors included in the error term. In other words, there might be unmeasured factors related to, for example, cost of inputs, local prices, and local infrastructure that could be responsible for endogeneity problems. If that were the case, then the use of ordinary least square estimators would not only produce biased estimates, but they would also be inconsistent.

The instrumental variable must be partially correlated with C_i, i.e. the coefficient on Z_i must be nonzero, $\gamma \neq 0$, so $\mathrm{Cov}(Z_i, u_i^C) \neq 0$, while Z_i must be uncorrelated with L_i, i.e. $\mathrm{Cov}(Z_i, u_i^L) = 0$. Thus, selecting an appropriate instrument becomes a crucial task for the estimation procedure. In order to test for endogeneity, we initially followed a Hausman specification procedure (Hausman, 1978), in which a linear projection of equation (1) is estimated, including the instrumental variable z, to obtain the reduced form coefficients. Since $\mathrm{Cov}(Z_i, u_i^L) = 0$, then we can get the predicted residuals, R_i, which in turn are included in equation (2) alongside the rest of the explanatory variables as follows:

$$L_i = \alpha_L + X_i \beta_L + C_i \delta + R_i \upsilon + e_i \tag{3}$$

where $e_i \equiv u_i^L - E(u_i^L | R_i)$ and (e_i, R_i) are assumed to be independent of X_i, i.e. $E(e_i | X_i, R_i) = 0$. A simple way to test for endogeneity is under the null of no endogeneity, $H_0 : \upsilon = 0$, following the usual two-stage least squares (2SLS) heteroskedasticity-robust t statistic. This is similar to the method proposed by Heckman (1979); in which the maximum amount of credit borrow, C_i, in (1) is transformed into a dichotomous variable, I_i, with value $I = 1$ for treatment households and

Table 1. 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 labor invested in production, including labor hiring	148	5.169	1.653	0	7.352
LGWAGEXP	Logarithm of household expenditure on labor-hiring per month	148	1.107	2.672	0	8.556
WAGEXP	Household expenditure on labor-hiring per month (in 2004 pesos)	148	314.2905	903.9844	0	5,200
SCHOOLING	If household has stopped sending children to school = 1	148	0.270	0.446	0	1
LGEARNINGS	Logarithm of household earnings per month	148	8.0879	1.016	5.011	10.150
EARNINGS	Household earnings per month (in 2004 pesos)	148	4990.73	4721.016	150	25,600
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
TIMEBUS	Years in business	148	5.162	5.746	0	30
DEPENDRATIO	Dependency ratio (number of children, students and old members / household size)	148	0.498	0.222	0.125	1
WOMAN	If borrower is woman = 1	148	0.730	0.446	0	1
Contained in K_i						
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
GROUP						
LGRATE	Logarithm of interest rate	148	3.151	0.041	3.091	3.178
Instrumental variable						
DISTANCE	Distance from branch to place of residence or business (in minutes)	148	32.365	21.716	10	100

$I = 0$ for the corresponding control group. Since both groups are program participants, then the function of labor supply in (2) can be derived as $L_{1i} = X_i\beta_1 + I_i\delta + u_{1i}$ for treatment households, and as $L_{2i} = X_i\beta_2 + u_{2i}$ for the control group, where

$$E\langle L_{1i} | I_i = 1\rangle - E\langle L_{2i} | I_i = 0\rangle = X_i(\beta_1 - \beta_2) + \sigma^* \phi(Z_i\gamma)/\Phi(Z_i\gamma) + V \quad (4)$$

and $\phi(\cdot)$ and $\Phi(\cdot)$ are the density of the distribution function and the cumulative distribution function of the standard normal, respectively. Note that $E(V) = 0$, whereas $\sigma^* = (\sigma_{2s} - \sigma_{1\varepsilon})$ is derived from the covariance matrix as in Maddala (1999, p. 261), which enables one to estimate the inverse Mills ratio, $\lambda(\cdot) \equiv \phi(\cdot)/\Phi(\cdot)$, resulting from the relationship between $\phi(\cdot)$ and $\Phi(\cdot)$. As Heckman suggests, we can estimate the β's and γ by exploiting the properties of the first stage Probit in order to obtain the inverse Mills ratio. In the second stage, we obtain consistent β's and the parameter of interest, δ, by adding the inverse Mills ratio in (2) as follows:

$$L_i = \alpha_L + X_i\beta_L + I_i\delta + \lambda \mathrm{M} + u_i^L \quad (5)$$

which is similar to the Hausman procedure discussed above; however, the 2SLS heteroskedasticity-robust t statistic is applied now on the inverse Mills ratio: when $\lambda \neq 0$, we have endogeneity problems.

Since we were interested in estimating the cumulative effects of microcredit, our survey collected a continuous variable that captures the length of membership, and which measures the number of years of program participation. This variable, M_i, was included in equation (1) to substitute C_i as the impact variable. However, because borrowers that had just joined the microcredit program integrate into our control group, M_i takes now a maximum value and a lower threshold zero in the form of a censored variable with value $M_i > 0$ for treatment households and $M_i = 0$ for control groups. For this particular reason, we adopted a Tobit approach (Tobin, 1958), which assumes that the probability of observing $M_i > 0$ and $M_i = 0$ is $\phi(\cdot)$, and $p\left(M_i^* < 0\right) = \Phi(0)$, 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 Heckman model, however, now the log-likelihood function takes the form:

$$L = \sum_{M_i > 0}\left(-\ln\sigma + \ln\phi\left(\frac{M_i - X_i\beta_M}{\sigma}\right)\right) + \sum_{M_i = 0}\ln\left(1 - \Phi\left(\frac{X_i\beta_M}{\sigma}\right)\right) \quad (6)$$

that generates the conditional mean function of the observed dependent variable M_i that can be used to estimate the determinants of the length of membership by treatment and control groups alike,[3] through the estimation of the marginal effects of X_i on M_i, i.e. $\partial E[M_i|X_i]/\partial X_i = \beta_M\Phi(X_i\beta_M/\sigma)$. This allows us to re-estimate equation (1) as:

$$M_i = \alpha_M + X_i\beta_M + Z_i\gamma + u_i^M \quad (7)$$

and the labor supply equation in (3) as:

$$L_i = \alpha_L + X_i\beta_L + M_i\delta + R_i\nu + \varepsilon_i \quad (8)$$

where R_i and ν are the predicted Tobit residuals and their parameter estimate, respectively. Note that the predicted residuals, which are estimated from (7) are included in

(8) as another regressor in order to test, in similar fashion as in the Hausman procedure, the null of no endogeneity. This type of method is what Amemiya (1984) has referred to as the Type III Tobit Model.

For empirical assessment, we have included in (1) and (7) a vector of credit market characteristics, K_i, that captures the effect of credit from moneylenders and other financial organizations. The rationale behind including K_i in the impact equation relies on the fact that if we do not control for the effects of other agents that actively compete with microcredit programmes, the parameter δ may be inconsistent. In addition, we have included a dummy variable that captures the effect of group lending *vis-à-vis* individual lending, and which is used to assess the effectiveness of alternative lending technologies in the context of urban poverty.

The Identifying Instrument

As an instrumental variable, we identified a continuous variable that measures the time participants spend traveling from the place where they live (or work) to the branch or place where group meetings took place, as a proxy for *accessibility* (in terms of *distance*) to credit, capturing the spatial dimension of urban credit markets.[4] Our argument relies on the fact that as an exogenous rule microcredit program usually concentrate on a geographical space to reduce the informational costs related to screening, monitoring, and enforcement activities, and hence restrict program participation to households living within a given operational radius.This is relevant when considering that periodical repayment schedules are extensively used as a monitoring device among microcredit program. Other studies have employed instrumental variables that respond to specific market, infrastructure, and demographic attributes that predominantly reflect rural conditions, such as land ownership (Pitt and Khandker, 1996) and household eligibility at the village level (Zaman, 1999). However, given the urban characteristic of our study, these instruments would have been, if adopted, inappropriate for empirical analysis.

When equation (1) was estimated following the Hausman, Heckman and Tobit procedures, 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 and the identifying instrument; however, when the instrument was included in equation (2), the parameter estimate γ accepted the null of no correlation against L_i (see Table 2).[5] As a result, we were able to use distance as the identifying instrument to test for the underlying assumption of no endogeneity.

As both the inverse Mills ratio and the predicted residuals presented in Table 3 report significant parameter estimates, there seems to be unobservable factors relegated to the error terms affecting the labor supply function. As a result, we focus on equations (3), (5), and (8) rather than (2). Note that under the Heckman (equation 5), the parameter δ measures the average impact of program participation on labor supply; however, it does not take into account the effect of progressive lending. Borrowers with say 5 years of program participation are expected to report greater impacts than those borrowers with just 1 or 2 years of membership. The inclusion of equations (3) and (8) in the impact analysis, in which the slope coefficient δ captures the effect of the maximum amount of credit borrowed and the length of membership, respectively, allow us to overcome this constraint. For that reason, the Hausman and Tobit are the preferred methods for analysis, although we present the Heckman model in Table 3 for comparative purposes.

Table 2. Identification of DISTANCE as Instrumental Variable

	Heckman		*Hausman*		*Tobit*	
Variable	*Eq. (1)*	*Eq. (2)*	*Eq. (1)*	*Eq. (2)*	*Eq. (1)*	*Eq. (2)*
DISTANCE	0.007	−0.004	0.012	−0.003	0.012	−0.002
	(4.28)***	(1.29)	(4.54)***	(1.15)	(1.76)*	(0.78)
LGMAXCREDIT		0.036		0.138		
		(2.33)**		(1.96)*		
MEMBERSHIP						0.080
						(1.92)*
LGRATE	−1.508	−7.156	−10.280	−6.392	−14.485	−6.936
	(1.20)	(3.59)***	(4.06)***	(3.08)***	(2.99)***	(3.44)***
TIMEBUS	0.001	0.025	0.002	0.025	0.004	0.025
	(0.15)	(2.04)**	(0.15)	(2.00)**	(0.13)	(2.02)**
AVEDU	−0.009	−0.012	−0.006	−0.013	−0.045	−0.012
	(0.74)	(0.71)	(0.31)	(0.78)	(1.06)	(0.67)
HOWNER	0.060	0.094	0.250	0.086	0.597	0.086
	(0.62)	(0.67)	(1.54)	(0.59)	(1.63)	(0.60)
DEPENDRATIO	−0.050	0.205	−0.466	0.239	−0.267	0.175
	(0.25)	(0.76)	(1.40)	(0.87)	(0.35)	(0.64)
WOMAN	0.156	−0.136	0.144	−0.094	1.119	−0.136
	(1.40)	(0.91)	(0.68)	(0.64)	(2.66)***	(0.88)
FORMALCREDIT	−0.183	−0.209	−0.674	−0.176	−0.998	−0.214
	(1.07)	(1.33)	(2.72)***	(0.99)	(1.33)	(1.30)
MONEYLENDER	−0.369	0.139	−0.280	0.082	−1.416	0.092
	(2.68)***	(0.82)	(1.03)	(0.47)	(2.24)**	(0.54)
GROUP	−0.163	−0.548	−1.417	−0.436	−1.025	−0.571
	(1.40)	(2.51)**	(7.71)***	(1.75)*	(2.30)**	(2.56)**
CONSTANT		28.228	41.394	24.742	46.003	27.621
		(4.44)***	(5.19)***	(3.64)***	(3.00)***	(4.30)***
Observations	148	148	148	148	148	148
Pseudo R^2/R^2	0.10	0.24	0.35	0.23	0.05	0.22
Wald/F/LR χ^2	30.77	3.70	14.21	3.40	24.77	3.18
Prob > χ^2 / >F / > χ^2	0.000	0.000	0.000	0.000	0.005	0.000

Notes: Dependent variable in (1): logarithm of the maximum amount of credit (LGMAXCREDIT). Note, however, that the Heckman procedure transforms LGMAXCREDIT into a dummy variable for treatment group = 1 if $I_i > 0$. Dependent variable in (2): logarithm of units of labor (LGAGHOURSPM). Robust z statistics in parentheses. *,**,*** Denote degrees of significance at 10%, 5%, and 1% respectively.

5. The Impact of Microcredit on Labor Supply

As both the units of labor supplied, L_i, and the maximum amount of credit, C_i, are in logarithmic form, the parameter estimate δ in equation (3) 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, although the magnitude of the responsiveness is inelastic. More precisely, the results suggest that if the maximum amount of credit goes up by 1%, and the unit of labor supplied is predicted to increase in the order of 0.42%, *ceteris paribus*. The results from the Heckman procedure in (5) report the difference in the mean log of units of labor, which can be used to estimate the percentage change in units of labor efficiency supplied by treatment

Table 3. The Impact of Credit on Labor Supply

	Reduced form equations			*Impact equations*		
Variable	*Hausman Eq. (1)*	*Heckman Eq. (1)*	*Tobit Eq. (7)*	*Hausman Eq. (3)*	*Heckman Eq. (5)*	*Tobit Eq. (8)*
LGMAXCREDIT				0.421	0.042	
				(2.93)***	(2.71)***	
MEMBERSHIP						0.091
						(1.71)*
GROUP	–1.417	–0.163	–1.025	–0.144	–0.179	–0.162
	(7.71)***	(1.40)	(2.30)**	(0.77)	(1.12)	(1.02)
AVEDU	–0.006	–0.009	–0.045	–0.009	–0.015	–0.001
	(0.31)	(0.74)	(1.06)	(0.52)	(0.90)	(0.08)
HOWNER	0.250	0.060	0.597	0.000	0.123	–0.029
	(1.54)	(0.62)	(1.63)	(0.00)	(0.83)	(0.18)
DEPENDRATIO	–0.466	–0.050	–0.267	0.507	0.302	0.335
	(1.40)	(0.25)	(0.35)	(1.67)*	(1.02)	(1.14)
WOMAN	0.144	0.156	1.119	–0.184	–0.290	–0.410
	(0.68)	(1.40)	(2.66)***	(1.23)	(2.07)**	(2.61)**
TIMEBUS	0.002	0.001	0.004	0.024	0.024	0.023
	(0.15)	(0.15)	(0.13)	(1.84)*	(2.00)**	(1.74)*
FORMALCREDIT	–0.674	–0.183	–0.998			
	(2.72)***	(1.07)	(1.33)			
MONEYLENDER	–0.280	–0.369	–1.416			
	(1.03)	(2.68)***	(2.24)**			
LGRATE	–10.280	–1.508	–14.485			
	(4.06)***	(1.20)	(2.99)***			
DISTANCE	0.012	0.007	0.012			
	(4.54)***	(4.28)***	(1.76)*			
INVERSE MILLS RATIO					–0.556	
					(2.49)**	
PREDICTED RESIDUALS				–0.287		–0.171
				(1.83)*		(1.95)*
CONSTANT	41.394		46.003	1.712	4.994	5.434
	(5.19)***		(3.00)***	(1.28)	(19.23)***	(22.85)***
Observations	148	148	148	148	148	148
R^2/Pseudo R^2	0.35	0.10	0.05	0.17	0.16	0.15
F test/LR χ^2	14.21	30.77	24.77	3.55	3.61	3.06
Prob > F/χ^2	0.000	0.000	0.005	0.001	0.000	0.003

Notes: Dependent variable in (1): logarithm of the maximum amount of credit (LGMAXCREDIT). The Heckman procedure transforms LGMAXCREDIT into a dummy variable for treatment group = 1 if $I_i > 0$. Dependent variable in (7): length of membership in years (MEMBERSHIP). Dependent variable in (3), (5), and (8): logarithm of units of labor (LGAGHOURSPM). Robust t statistics in parentheses. *,**,*** Denote degrees of significance at 10%, 5%, and 1% respectively.

households relative to the control group. In order to do so, we followed Halvorsen and Palmquist (1980) to obtain the antilog of δ, $(e^{0.042}) = 1.0428$, that suggests that the median value of hours of labor supplied bya treatment household in the production of a market good is higher than that of the control groups by about 4.3%, *ceteris paribus*.

Similarly, the parameter δ in equation (8) captures the semilog of units of labor efficiency with respect to the length of membership. This implies that the slope coefficient of M_i measures the constant proportional or relative change in the number of units of labor efficiency for a given absolute change in the length of program participation. The results suggest that, *ceteris paribus*, the number of units of labor efficiency employed by enterprising households increases, on average, at the annual rate of 9.1% after joining the microcredit program. We computed the compound rate of growth using the antilog of δ, which resulted in an annual growth rate in units of labor efficiency in the order of 9.5%. Since the constant reflects the log of units of labor at the beginning of program participation, by taking its antilog we estimate the average number of hours invested by control households. We predict this value at approximately 228 hours per month. After 1 year of program participation, an enterprising household was able to increase the number of units of labor in production from 228 to 250 hours per month.

It is apparent that not only access to credit but also the length of program membership is associated with improvements in the allocation of labor resources. However, an increased allocation of labor resources could also reveal some indirect routes through which microcredit-impact poor laborers hired by loan-supported enterprising households. In order to explore this question, we collected information about household expenditure on labor hiring, which is computed as the product of the number of units of labor hired and the wage rate paid per unit of labor, $W = L^h\lambda(w)$.[6] In a preliminary examination, we found that just about 15% of the sample of participating households did actually hire laborers outside the family. This is in line with the cost function of labor efficiency discussed earlier in section 1, in which W_i takes a maximum value and a lower threshold zero in the form $W_i = \max\left(W_i^*, 0\right)$; with the value $W_i^* > 0$ if a household reports expenditure on labor hiring, and $W_i^* = 0$, otherwise. Given that we encounter a *censored* sample problem, we adopt a method similar to the first-stage Tobit selection equation specified in equation (7) but now taking the form:

$$W_i = \alpha_w + Y_i\psi_w + X_i\beta_w + u_i^w \tag{9}$$

where Y is a continuous variable measuring monthly household earnings, and X is the same vector of household characteristics derived in (7). α_w, ψ_w, β_w, and u_i^w are, respectively the intercept, slope coefficients, and error term. Because we have a data-censoring case demanding a homoskedastic normal distribution, we transform W_i into logarithmic form to make this assumption more reasonable. The reason for following a standard Tobit reflects our interest in analyzing the conditional mean function of household expenditure on labor hiring, which is censored at zero for self-employing households, but has normally distributed disturbances (Greene, 2003). The empirical results are presented in the following section.

6. The Impact of Microcredit on Labor Hiring

As both expenditure on labor hiring and earnings are in logarithmic form, the parameter estimate ψ in equation (9) measures the elasticity of *latent* expenditure on labor efficiency with respect to household earnings (equation (9c) in Table 4). This equation captures the *indirect* route through which microcredit impacts household expenditure on labor. If microcredit becomes a significant determinant in rising household earnings, then it is reasonable to assume that after reaching the upper limit

Table 4. Determinant of Labor Expenditure

Variable	*Tobit Eq. (9a)*	*Tobit Eq. (9b)*	*Tobit Eq. (9c)*	*Tobit Eq. (9d)*
LGMAXCREDIT	2.660			
	(1.77)*			
MEMBERSHIP		1.120		
		(0.97)		
LGEARNINGS			5.811	
			(3.02)***	
EARNINGS				0.278
				(3.56)***
TIMEBUS	0.461	0.444	0.310	52.175
	(1.99)**	(1.92)*	(1.45)	(0.80)
AVEDU	0.575	0.565	0.275	84.117
	(1.55)	(1.51)	(0.82)	(0.82)
HOWNER	–2.900	–2.158	–2.457	–607.976
	(0.91)	(0.67)	(0.85)	(0.71)
DEPENDRATIO	1.807	–0.093	2.119	232.882
	(0.29)	(0.01)	(0.37)	(0.13)
WOMAN	–6.981	–7.771	–3.909	–1,247.087
	(2.02)**	(2.13)**	(1.26)	(1.32)
GROUP	–0.519	–1.764	–1.529	–39.583
	(0.15)	(0.53)	(0.51)	(0.04)
CONSTANT	–35.273	–11.596	–58.408	–4,500.426
	(2.23)**	(2.05)**	(3.23)***	(2.71)***
Observations	148	148	148	148
Pseudo R^2	0.06	0.05	0.11	0.05
LR χ^2	16.35	13.90	26.49	25.58
Prob > χ^2	0.022	0.053	0.000	0.000

Notes: Dependent variable in (9a–10c): logarithm of household expenditure on labor. Dependent variable in (9d): household expenditure on labor in 2004 pesos. Absolute value of *t* statistics in parentheses. *,**,*** Denote degrees of significance at 10%, 5%, and 1% respectively.

of labor supply, enterprising households begin to consider hiring laborers outside the family. We have estimated equation (9) with, C_i and M_i as explanatory variables in order to capture the direct (linear) effects of microcredit on labor hiring. In the former case, the slope coefficient measures the elasticity of a household's expenditure on labor hiring with respect to credit (equation (9a) in Table 4), whereas in the latter, the slope coefficient measures the effect of one additional year of program participation on the number of units of labor hired (see equation (9b) in Table 4).

The results show that a 1% increase in the amount of credit borrowed gives rise to a 2.6% increase in expenditure on labor hiring, and the results are statistically significant at the 10% level; however, when the same equation was estimated with the length of membership as the impact variable (equation (9b) in Table 4), the slope coefficient became statistically insignificant although its magnitude suggests that there might be a positive impact. Our results are thus inconclusive to confirm significant (and direct) effects of microcredit on wage employment. We did find, nonetheless, a large and significant elasticity of household expenditure on labor with respect to earnings. Other things held constant, a 1% increase in household earnings is predicted to

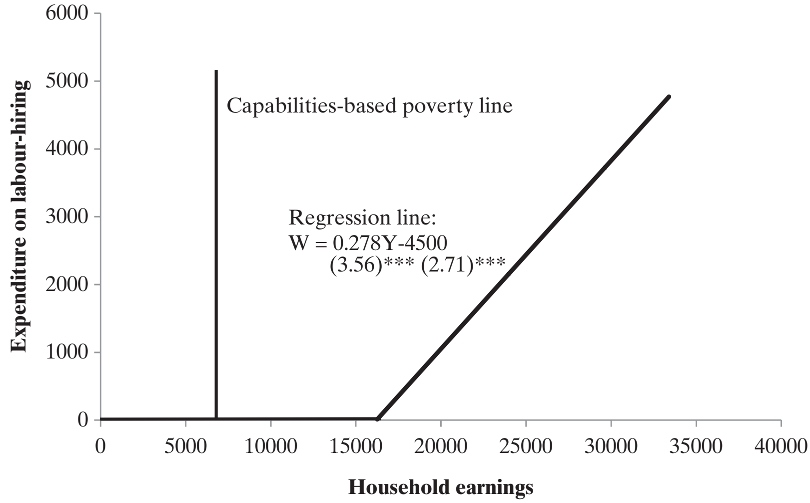

Figure 1. The Relationship between Household Earnings and Expenditure on Labour-hiring (Figures in 2004 pesos)

give rise to a 5.8% increase in expenditure on labor hiring. The large elasticity can be explained by the low wage rate paid to poor laborers relative to household earnings, which reflects the degree of welfare inequality in urban poverty Mexico. Most variables contained in the vector of household characteristics fail to report significant coefficients, a fact that reflects the relative homogeneity among households participating in the study.

Although the computed elasticities reported in Table 4 provide valuable information about the relationship between household earnings and expenditure on labor, we still do not know at what level of earnings enterprising households employ laborers. In order to estimate that minimum level of earnings, we transformed the logs of W_i and Y_i into linear variables, and computed equation (9) accordingly. The results are shown in Figure 1 and in equation (9d), Table 4.

The slope coefficient ψ now reports the predicted values of an absolute change in household expenditure on labor-hiring conditional on an absolute change in earnings. As we hypothesized in section 2, at low levels of household earnings, no household is willing to hire laborers for a relatively high cost of buying units of labor efficiency, and therefore, self-employment remains dominant. Enterprising households will hire laborers only after reaching a minimum level of earnings, a level at which the cost of labor efficiency is affordable. We envisage that level of earnings as a platform for employment generation. Our estimations suggest that, in the context of urban poverty in Mexico, the platform is located at about 16,250 pesos per month (around US$1,480). This level of household earnings is well above the poverty line; in fact, about three times the capability-based poverty line (z_2) derived for urban areas in Mexico, which is a threshold that adds to the food-based poverty line (z_1) that measures extreme deprivation, a non-food component that includes expenditure on clothing, housing, health care, education, and public transport (Sedesol, 2002).[7] After that income level, the propensity of expenditure on labor-hiring becomes positive and significant: a one-peso increase in the level of household earnings is predicted to give rise to 28 cents of labor expenditure, *ceteris paribus*. It is apparent that among low-income households, the cost of hiring efficient labor is too high as an option for production. In the context of Africa, Mosley and Rock (2004, p. 477) report vulnerable non-poor enterprising households being reluctant to employ workers due to "a very considerable perceived risk associated with the initiation of financial relationships going outside the family." Our study shows that the vulnerable non-poor employ laborers after reaching an upper limit of labor supply, and after achieving a welfare status well above the poverty line.

Although we found no evidence of poor households hiring laborers, we did find that almost one-third of laborers hired by loan-supported (and non-poor) enterprising households were suffering from extreme deprivation, i.e. with incomes below z_1,[8] whereas 60% of hires reported incomes below an asset-based poverty line (z_3)[9] that measures "moderate" povertyin urban Mexico (Sedesol, 2002). Important differences were also identified between treatment and control groups in relation to the wage paid to poor laborers: taking the capability-based poverty line as a reference point, we observed that poor laborers employed by treatment households received wages 25% above that poverty line, whereas the corresponding control groups paid wages far below that threshold, in the order of 64% of the poverty line. Laborers employed by treatment households worked on average 34 hours per week relative to 20 hours reported from workers employed by control groups. It is apparent that by participating in a microcredit program, non-poor enterprising households increase the allocation of labor resources up to a level that benefit poor laborers. However, although wage differentials are associated with the intensity of labor, efficiency factors may also drive up the wage rate.

Labor Intensity vs Labor Efficiency

As household expenditure on labor is given by the product $L^h\lambda(w)$, where L^h is the number of units of labor hired, and $\lambda(w)$, the wage rate per unit of labor, conditional on efficiency factors, we can derive the elasticity of the wage rate, relative to the number of units of labor hired, $d(\ln w)/d(\ln L^h)$, to estimate the relative change in labor efficiency among poor laborers. If the elasticity is greater than one, efficiency factors may be driving up the wage rate. Our estimations report an elasticity equal to 1.19, suggesting that enterprising households not only increase expenditure on labor as a result of higher labor intensity, but also owing to efficiency factors. However, the proximity of the elasticity to the unity implies that such efficiency factors (if any) are rather modest.

7. Concluding Remarks

Our study has provided insights into the dynamics involving credit markets and labor, with important implications for anti-poverty policy. First, after controlling for endogeneity constraints, we find positive and significant impacts of microcredit on labor supply that are associated with the length of program participation. This implies that not only credit access but also membership duration is an important determinant in an increased allocation of labor resources, with implications for the welfare status of loan-supported enterprising households.

Second, an increased allocation of labor resources also reveals indirect routes through which microcredit impact extreme poverty in urban markets. If by borrowing capital, enterprising households increase production (and hence earnings) up to a level that they cannot supply the units of labor required for production by themselves, then the marginal propensity to hire labor becomes significant. However, we observed that behavior only after households cross an income threshold estimated to be at a level three times as high as the poverty line. We envisage income threshold as a platform for employment generation in urban poverty Mexico.

Third, we find significant differences between wages paid by treatment and control households. While laborers employed by control households received wages well below the poverty line, laborers hired by treatment households reported wages above such a threshold. Two factors appear to explain wage differences. The first is associated with labor intensity. Laborers hired by treatment households report more hours at work *vis-à-vis* laborers hired by control groups. The second is associated to labor efficiency. We find an elastic response of wages relative to the number of hours worked, suggesting that there might be efficiency factors driving up the wage rate. The implications for policy are relevant in the sense that poverty targeting in microcredit may actually miss out important trickle-down effects through labor markets that can benefit poor laborers. By relaxing poverty targeting and extending the market reach to the vulnerable non-poor and non-poor, microcredit programs could, through the labor markets, indirectly contribute to alleviate poverty in urban areas.

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Notes

1. Hulme and Mosley (1996) initially proposed this sample strategy in the context of impact analysis of microcredit.
2. For a detailed description of the participating organizations and the content of the survey questionnaire, see Niño-Zarazúa (2009).
3. McDonald and Moffitt (1980) have decomposed equation (6) into two parts to obtain the effects of a change in X_i on (1) the conditional mean of M_i, and (2) the probability that the observation will fall in the part of the distribution where $M_i > 0$.
4. The mean value for this time-dimensional variable was 22 minutes for an outward journey.
5. We adopted Lawrence Klein's rule of thumb (1961), to test the instrumental variable for potential collinearity problems; however, we did not find evidence of severe collinearity.
6. Since we cannot observe λ, we assume that this factor is captured by the wage rate w.
7. This poverty line is estimated at 6,570 pesos per month for an average household, which is the product of the capability-based poverty line derived at 1,507.5 pesos of 2004 and the household size, which is weighted by equivalence factors as in Rothbarth (1943).
8. The food-based poverty line is derived from a basic food basket with a value estimated at 784.5 pesos of 2004.
9. The asset-based poverty line is derived by adding to the food-based poverty line, a mean value of a non-food component, through the Engel method. This threshold of "moderate" poverty is set at 1,881 pesos of 2004.