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Microcredit, labour, and poverty impacts in urban Mexico

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September 2009

BWPI Working Paper 103

Creating and sharing knowledge to help end poverty

Brooks World Poverty Institute
ISBN : 978-1-907247-02-6

www.manchester.ac.uk/bwpi

Abstract

Improved household accessibility to credit is identified as a significant determinant of intra-household re-allocation of labour 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 programmes can indirectly benefit poor labourers through increased employment. Second, we conduct the study in the spatial dimension of urban poverty Mexico. This is relevant when considering that, unlike in rural areas, labour often represents the only source of livelihoods to the extreme poor. Our findings point to significant trickle-down effects of microcredit that benefit poor labourers; however, these effects are only observed after loan-supported enterprising households achieve earnings well above the poverty line. The paper concludes with reflections on the policy implications.

JEL Classification: C24; C25; C81; O16; O17; O18

Keywords: Mexico; microcredit; labour; poverty

Miguel Niño-Zarazúa is a Research Fellow at the Brooks World Poverty Institute, The University of Manchester.

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Acknowledgements

We would like to thank Malcolm Harper, Karl Taylor and Jenny Roberts and seminar participants at the Universities of Sheffield, Manchester, and Stockholm for valuable comments on previous versions of this paper. Special thanks are due to Armando Barrientos whose suggestions greatly contributed to improving this paper. MNZ gratefully acknowledges financial support from the National Council of Science and Technology of Mexico. All the errors are ours.

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 'banked', only a small percentage had access to credit. Credit rationing implies that households in poverty are not able to allocate their labour resources optimally. In this context, the improved availability of microcredit to these groups should lead to a re-allocation of their labour 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 due to labour-market rigidities. Khandker *et al* (1998) for instance, find 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) have argued that this is partly because at low levels of income, enterprising households can only afford to employ unskilled and malnourished labourers with very low productivity. Informational constraints regarding the productivity of potential hires may also prevent enterprising households from hiring labour, with self-employment perceived as the less risky choice. However, if the household reaches the upper limit of its available labour supply, then new hires can emerge as a strong alternative for production, with implications for the poverty status of poor labourers. Mosley and Rock (2004), for example, report significant impacts on poor labourers employed by loan-supported enterprising households, members of microcredit programmes operating in Africa. The extent to which microcredit leads to increased employment among the extreme poor in urban markets is crucial, especially as labour supply often represents the only source of livelihoods for this group.

This paper explores this issue using primary data collected from three microcredit programmes operating in Mexico. The study contributes to the literature on the impact of microcredit on poverty in two important respects: first, the paper explores this issue in the spatial dimension of urban poverty. This is critical when considering that, unlike in rural markets; labour often represents the only source of livelihoods to the highly mobile extreme poor. We exploit this spatial dimension to deal with endogeneity problems in the econometric estimation procedure presented in Section 3. Second, we investigate the routes through which microcredit reaches those in extreme poverty outside the household. We test whether, by lending to vulnerable non-poor enterprising households, microcredit organisations can indirectly benefit poor labourers through increased employment.

The remainder of this paper is organised as follows: Section 1 presents the analytical framework in which the relationship between microcredit and labour supply is examined. Section 2 describes the quasi-experimental research design, which enables the empirical work to deal with selection bias and endogeneity problems. In Section 3, the econometric procedure is discussed, whereas in Sections 4 and 5, the impacts on labour supply and labour-hiring are analysed, respectively. Section 6 concludes with reflections on the policy implications.

1. Microcredit and labour supply

As a starting point for the examination of the relationship between microcredit and labour 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 labour 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 technology changes, at least in the short-term, so α is assumed to be constant.

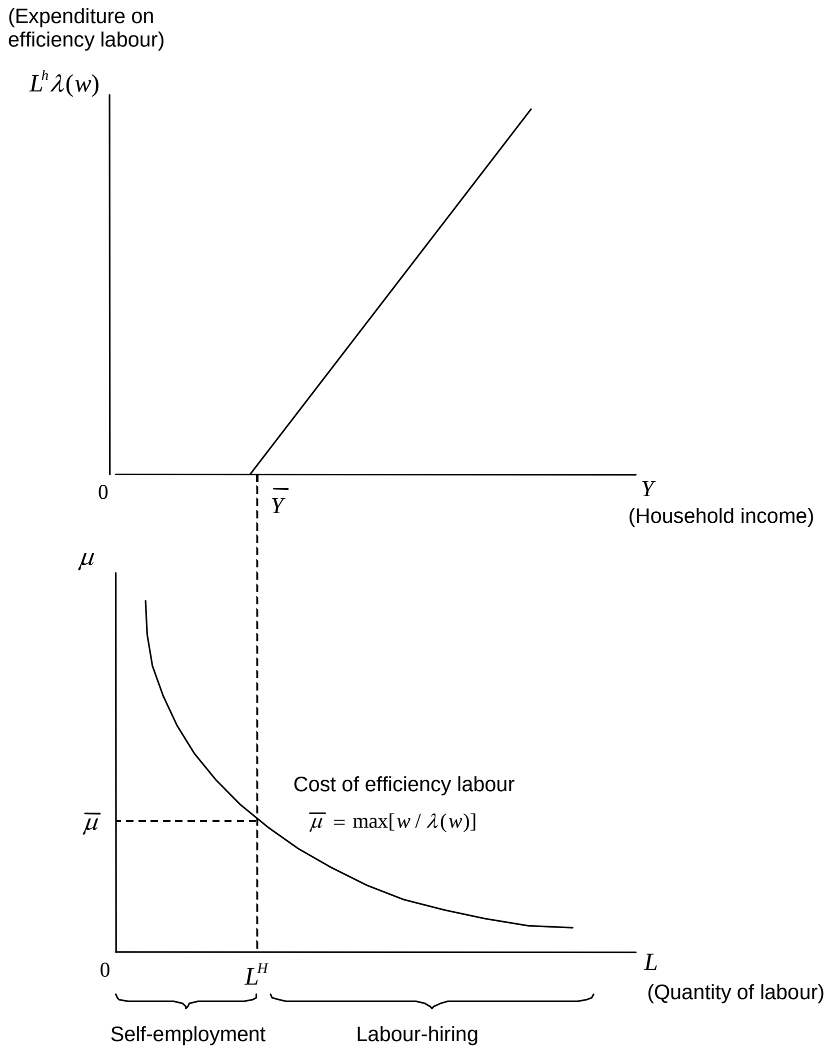
In the production of y, the enterprising household is assumed to supply the amount of labour L^H, constrained to the number of household members of working-age, i. This can be observed in the form of an upper limit of hours-work, h, and defined as $L^H \geq \underset{i,h}{\mathrm{Max}}\, \mathrm{N}\left[i(h)\right]$. This constraint implies that under self-employment, labour supply is equal to the number of hours-work contributed by household members of working-age, that is, $L = L^H$. As α is assumed to be constant, an injection of capital from microcredit should increase the labour supply up to the upper limit L^H, point at which the household reaches an optimal allocation of internal labour resources. But if more labour is required due to an increase in production, then hiring labourers outside the household becomes a sensible choice. Note, however, that new hires are not only a function of household earnings from production but also of the cost of hiring efficiency labour. Leibenstein

(1957), Mazumdar (1959), and Dasgupta (1993) have pointed out that labour efficiency is conditional upon factors such as nutritional status, individual abilities, skills and efforts that determine labour productivity. Dasgupta and Ray (1986) have also shown that at low levels of household earnings, non-poor enterprising households that are considering employing labourers as a result of having reached their upper limit of labour supply could find that they can only afford to employ workers with very low productivity. Informational asymmetries can also constrain the demand for labour 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, behaviour, or moral integrity, and for that reason they may simply choose to self-employ and produce at sub-optimal levels.

Since our primary interest is not only to assess the direct effects of microcredit on labour supply, but also the indirect routes through which microcredit impact poor labourers hired by loan-supported households, we derive a cost function for efficiency units of hired labour, $\mu = w/\lambda(w)$ 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 labour efficiency, *labour efficiency,* λ. In the context of fragmented labour markets, these productivity and informational constraints are expected to exacerbate the relative cost of efficiency labour, 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, $\overline{Y}$, the level at which they can afford to pay for this cost.

New hires are observed in the form of household expenditure on labour-hiring, denoted by W, which is the product of units of efficiency labour hired (L^h) and the wage rate, conditional upon efficiency factors, that is, $W = L^h\lambda(w)$. This function is similar to that in Dasgupta and Ray (1986); however, in our case the cost function takes a maximum value $\overline{\mu}$ and a lower threshold that is censored at zero for households that self-employ, $\overline{\mu} = \max[w/\lambda(w), 0]$, implying that at low levels of household earnings, from 0 to $\overline{Y}$ in the upper quadrant of Figure 1, no household hires labourers because they face high costs of buying efficiency units of labour, the area above $\overline{\mu}$, and hence they rely on their own labour resources for production, the area from 0 to L^H in the lower quadrant of Figure 1. But once enterprising households reach a minimum level of earnings, located at any point above $\overline{Y}$, they begin to consider employing workers with a minimum level of skills and abilities required for production. Thus, if $\overline{\mu}$ is affordable, then household expenditure on labour-hiring becomes positive, i.e., $L^h > 0$, and employment in the enterprise becomes $L = L^H + L^h$. Note that the further the distance from $\overline{Y}$ to Y, i.e., the higher the level of household earnings, the lower the relative cost of buying additional units of efficiency labour μ , and thus the higher the probability of observing new hires outside the family. Credit accessibility can play a crucial role in that process: If households are able to increase their earnings beyond the threshold $\bar{Y}$ as a result of borrowing capital from a microcredit programme, the likelihood of indirect poverty impacts, through labour markets, becomes promising. In Section 2, we describe the research design adopted to investigate this relationship.

Figure 1. The relationship between household income, and expenditure on efficiency labour



Source: Adapted from Dasgupta and Ray (1986)

2. Research design

We designed a quasi-experiment that is often referred to as a posttest only quasi-experiment, in which two groups of households are sampled: treatment and control (Campbell and Stanley 1966). A major problem that emerges from this type of research design 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 affect the selection process and thus the outcomes of interest. We refer to this potential problem as a demand-related bias. A fundamental assumption here is that participation in a microcredit programme 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 organisation, we may still face selectivity discrimination made by the lender or group members that screen out applicants who, for instance, may live outside the market radius where the microcredit programme operates. We refer to this potential problem as a supply-related bias. In this sense, the selection process can be defined by two elements: one related to a household's decision to participate or not in a microcredit program, and another associated with the decision of lenders (or group members) of whether or not to accept the applicant.

In the end, we were able to specify the distribution of households that had self-selected to participate in the credit programme, 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 accepted by the lender, and therefore were actively borrowing from the credit programme were eligible to be sampled as members of the treatment group. Similarly, those households who had self-selected to participate in the microcredit programme and had been accepted by the lender, but had just received (or were about to receive) 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 a geographical and temporal identification criterion. The geographical criterion consisted of operationalising the quasi-experiment among households living in the same neighbourhood, in areas with a degree of socio-economic

[1] Hulme and Mosley (1996) initially proposed this sample strategy in the context of impact analysis of microcredit.

homogeneity, where the comparison between treatment and control groups could be supported. By following this procedure, it was possible to hold constant factors such as infrastructure, local prices, and wages that could have otherwise exacerbated endogeneity problems. A high population density in urban areas made it possible to take this approach. The temporal criterion consisted of selecting a market area where the microcredit organisations had achieved a certain level of penetration and where the effects of microcredit could be more likely to be observed. In this sense, to have access to institutional information was crucial to identify the areas where the study could be conducted.

The sampling strategy was implemented using a multistage cluster procedure: first, we had access to a list of programme participants (both treatment and control) from three case-study organisations (the clusters) who 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. We were able to sample 148 households, 55 of which were members of Community Financial Services (Fincomun) and living in San Miguel Teotongo, a neighbourhood located to the eastern periphery of Mexico City; 46 members of Centre for the Assistance of the Micro-entrepreneur (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 members of Programs for Women (Promujer), and living in Tula City and the surrounding areas. Thus, we have three market locations, one for each case-study microfinance organisation (see Table 1).

It is important to point out that unlike CAME and Promujer (and most microcredit programmes operating in Mexico) that employ group lending methodologies, Fincomun mainly relies on individual lending technology, and demands as a result, physical (rather than social) collateral as enforcement mechanism. The inclusion of Fincomun in the impact study has allowed us to evaluate potential differences between group lending and individual lending technology regarding credit impacts on labour supply. We report our findings in Section 4. The questionnaire included questions on household characteristics, earnings, type of income generating activities, access and use of loans, labour supply, including hires from outside the household, wages, and other information needed for the purpose of the study[2]. In the following section, we discuss the econometric estimation procedure adopted to estimate the impacts of microcredit on labour supply.

[2] For a detailed description of the content of the questionnaire, see Nino-Zarazua (2007)

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
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

3. The econometric estimation

We begin the discussion by considering the following model:

$$C_i = \alpha_C + X_i\beta_C + Z_i\gamma + u_i^C \qquad (1)$$

$$L_i = \alpha_L + X_i\beta_L + C_i\delta + u_i^L \qquad (2)$$

where C_i measures the maximum amount of credit borrowed by household i, which is exogenously determined by the lender who defines that maximum threshold according to the level of programme participation. Note that both treatment and control groups are programme 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 efficiency labour invested in production, including labour-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 specialisation; 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 a woman (see Table 2).

Table 2. 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
WAGEXP	Household expenditure on labour-hiring per month (in pesos of 2004)	148	314.2905	903.9844	0	5200
SCHOOLING	If household has stop 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 pesos of 2004)	148	4990.73	4721.016	150	25600
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

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, that is, the coefficient on Z_i must be nonzero, $\gamma \neq 0$, so $Cov(Z_i, u_i^C) \neq 0$, while Z_i must be uncorrelated with L_i, that is, $Cov(Z_i, u_i^L) = 0$. Thus, selecting an appropriate instrument becomes a crucial and complex 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 (1) is estimated, including the instrumental variable Z, to obtain the reduced form coefficients. Since $Cov(Z_i, u_i^L) = 0$, 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:

$$L_i = \alpha_L + X_i\beta_L + C_i\delta + R_i\upsilon + e_i \qquad (3)$$

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, that is, $E(e_i | X_i, R_i) = 0$. A simple way to test for endogeneity is under the null of no endogeneity, $H_0 : \upsilon = 0$, following the usual 2SLS heteroskedasticity-robust t statistic. This is similar to the method proposed by Heckman (1979); in which the maximum amount of credit borrowed, C_i, in (1) is transformed into a dichotomous variable, I_i, with value $I = 1$ for treatment households and $I = 0$ for the corresponding control group. Since both groups are programme participants, then the function of labour 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

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

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 $\sigma^{*}=(\sigma_{2\varepsilon}-\sigma_{1\varepsilon})$ is derived from the covariance matrix as in Maddala (1977:261), which enables us 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 $\beta's$ and γ by exploiting the properties of the first stage Probit in order to obtain the inverse Mills ratio. In the second stage least square procedure, we obtain consistent β 's and the parameter of interest, δ , by adding the inverse Mills ratio in (2) as follows:

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

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 examining the impacts of credit over time, our survey collected a continuous variable that captures the length of membership, and which measures the number of years of programme 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 programme 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 adopt a Tobit approach (Tobin 1958), which implies that the probability of observing $M_i>0$ and $M_i=0$ is $\phi(\cdot)$, and $p(M_i^{*}<0)=\Phi(0)$, 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 Heckman procedure, however, now the log-likelihood function takes the form:

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

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 , that is, $\partial E\left[M_i \middle| X_i\right] / \partial X_i = \beta_M \Phi\left(X_i \beta_M / \sigma\right)$. 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 labour supply equation in (3) as:

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

where R_i and ν are the predicted Tobit residuals and their parameter estimate, respectively. Note that $\varepsilon_i \equiv u_i^L - E(u_i^L | R_i)$, where (ε_i, R_i) are assumed to be independent of X_i, that is, $E(\varepsilon_i | X_i, R_i) = 0$. The predicted residuals, which are estimated from the Tobit equation in (7) are then 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 organisations such as savings and credit associations. The rationale behind including K_i in the impact equation relies on the fact that if we do not control for the effects of agents that actively compete with microcredit programmes, then the parameter δ may be inconsistent, that is, we could wrongly attribute an outcome to the microcredit programme when in fact it comes from, for example, a moneylender. In addition, we have included a dummy variable that measures the effect of group lending with reference to individual lending, and which is used to assess the effectiveness of

[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 $M_i > 0$.

alternative lending technologies in the context of urban poverty. As discussed in Section 2, this was feasible due to the inclusion of Fincomun in the impact study.

3.1 The identifying instrument

As instrumental variable, we identified a continuous variable that measures the time participants spend travelling from the place they live (or work) to the branch, used as a proxy for accessibility (in term of distance) to credit, capturing the spatial dimension of urban credit markets[4] . Our argument relies on the fact that, as an exogenous rule determined by the lender, microcredit programmes usually concentrate on a determined geographical space in order to reduce the informational costs that are related to screening, monitoring, and enforcement activities, and hence restrict programme participation to households living within a given operational radius. This is particularly true when considering that periodical repayment schedules are extensively used as a monitoring device among microcredit programmes in Mexico and elsewhere. Other studies have employed instrumental variables that response to specific market, infrastructure, and demographic attributes that predominantly reflect rural conditions, such as land ownership (e.g. Pitt and Khandker 1998) and household eligibility at the village level (e.g. 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 3) [5]. As a result, we were able to use distance as the identifying instrument to test for the underlying assumption of no endogeneity.

[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.

Table 3. Identification of DISTANCE as instrumental variable

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 labour (LGAGHOURSPM)

	Heckman		Hausman		Tobit	
	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 R2 / R2	0.10	0.24	0.35	0.23	0.05	0.22
Wald / F / LR Chi2	30.77	3.70	14.21	3.40	24.77	3.18
Prob>chi2 / >F / >chi 2	0.000	0.000	0.000	0.000	0.005	0.000

Robust z statistics in parentheses

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

As both the inverse Mills ratio and the predicted residuals presented in Table 4 report significant parameter estimates, there seems to be unobservable factors relegated to the error terms affecting the labour supply function. As a result, the null of no endogeneity is rejected and hence the attention is focused on the results from equations (3), (5) and (8) rather than (2). Note however, that under the Heckman (equation 5), the parameter δ measures the average impact of programme participation on labour supply; however, it does not take into account the effect of progressive lending. Borrowers with say five years of programme participation are expected to report greater impacts than those borrowers with just one or two 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, has allowed us to overcome this constraint. For that reason, Hausman and Tobit are the preferred methods for analysis, although we present them alongside the Heckman model for comparative purposes. The empirical results are discussed in Section 4 and presented in Table 3.

4. The impact of microcredit on labour supply

As both the units of labour 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 labour (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 one percent, the units of labour supplied is predicted to increase in the order of 0.42 percent, *ceteris paribus*. The results from the Heckman procedure in (4) report the difference in the mean log of units of labour, which can be used to estimate the percentage change in units of efficiency labour supplied by treatment households relative to the control group. In order to do so, we followed Halvorsen and Palmquist (1980) to obtain the antilog of δ as follows: $(e^{0.042}) = 1.0428$, suggesting that the median value of hours of labour supplied by a treatment household in the production of a market good is higher than that of the control groups by about 4.3 percent, *ceteris paribus*.

Table 4. The impact of credit on labour supply

Dependent variable in (1): logarithm of the maximum amount of credit (LGMAXCREDIT)†
Dependent variable in (7): length of membership in years (MEMBERSHIP).
Dependent variable in (3), (5), and (8): logarithm of units of labour (LGAGHOURSPM).

	Reduced form equations			Impact equations		
	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
R2 / Pseudo R2	0.35	0.10	0.05	0.17	0.16	0.15
F test / LR Chi2	14.21	30.77	24.77	3.55	3.61	3.06
Prob > F / Chi2	0.000	0.000	0.005	0.001	0.000	0.003

Robust t statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%
† Note that the Heckman procedure transforms LGMAXCREDIT into a dummy variable for treatment group = 1 if $\mathbf{I}_i > 0$

Similarly, the parameter estimate δ in equation (8) captures the semilog of units of efficiency labour 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 efficiency labour for a given absolute change in the length of programme participation. The results suggest that, ceteris paribus, the number of units of efficiency labour supplied by enterprising households increases, on average, at the annual rate of 9.1 percent after joining the microcredit programme. In order to estimate the growth rate over the period of time treatment households had borrowed from the credit programme, we compute the compound rate of growth using the antilog of δ as follows: [(antilog(δ)-1)x100]. Our results predict an annual growth rate in units of efficiency labour in the order of 9.5 percent, which is slightly higher than that of 9.1 percent obtained from the instantaneous estimation. Since the constant reflects the log of units of labour invested at the beginning of programme participation, then by taking its antilog we can estimate the average number of hours invested by control households. We predicted this value at approximately 228 hours per month. In this sense, after one year of programme participation an enterprising household is able to increase, on average, the number of units of labour invested in production from 228 to 250 hours per month.

It is apparent that not only access to credit but also the length of programme membership is associated with improvements in the allocation of labour resources. An increased allocation of labour resources could nonetheless have adverse effects if this increase translates into a higher propensity of child labour particularly in the absence of appropriate enforcement of school attendance norms. While raising household income and reducing poverty in the short run, child labour will negatively affect human capital accumulation and therefore long-term sustained exit from poverty. Our argument relies on the strong association between school attainment and labour productivity reported in Spence (1973) and Schultz (1988). However, empirical evidence does not support the assumption of adverse effects, as the relationship between microcredit and schooling is being reported to be positive and significant (see Niño-Zarazúa 2007).

An increased allocation of labour resources could also reveal, as discussed earlier, some indirect routes through which microcredit impact poor labourers hired by loan-supported enterprising households. In order to explore this issue, we collected information about household expenditure on labour-hiring, which is computed as the product of the number of units of labour hired and the wage rate paid per unit of labour, $W = L^h \lambda(w)$ [6]. In an initial examination, we found that just about 15 percent of the sample of enterprising households did actually hire labourers outside the family. Note

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

that this is in line with the cost function of efficiency labour discussed earlier in section 1, in which W_i takes a maximum value and a lower threshold zero in the form $W_i = \max(W_i^*, 0)$; with value $W_i^* > 0$ if a household reports expenditure on labour-hiring, and $W_i^* = 0$, otherwise. Since we encounter a censored sample problem, we follow a method similar to the first-stage Tobit selection equation specified in equation (7) but now taking the form:

$$W_i = \alpha_w + Y_i\psi_w + X_i\beta_w + u_i^w \qquad (9)$$

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 analysing the conditional mean function of household expenditure on labour-hiring, which is censored at zero for households with no labour hiring, but has disturbances normally distributed. Note that the use of least squares for the sub-sample for which $W_i^* > 0$ would have produced inconsistent and bias estimators (Greene 2003). The empirical results are presented in the following section.

5. The impact of microcredit on labour hiring

As both expenditure on labour hiring and earnings are in logarithmic form, the parameter estimate ψ in equation (9) measures the elasticity of latent expenditure on efficiency labour with respect to household earnings (equation 9c in Table 5). This equation captures the indirect route through which microcredit impacts household expenditure on labour: If microcredit becomes a significant determinant in rising household earnings (as reported in Nino-Zarazua 2007), then it is reasonable to assume that after reaching the upper limit of labour supply (and crossing a minimum level of earnings, at which the cost of buying efficiency units of labour is affordable), enterprising households may begin to consider hiring labourers outside the family.

We have also estimated equation (9) with, C_i and M_i as explanatory variables in an attempt to capture any direct link between labour-hiring and microcredit. In the former case, the slope coefficient measures the elasticity of household's expenditure on labour-hiring with respect to credit (equation 9a in Table 5), whereas in the latter case, the slope coefficient captures the effect of one additional year of programme participation on the number of units of labour hired (equation 9b in Table 5). The results are presented in Table 5.

Table 5. Determinant of labour expenditure

Dependent variable in (9a -10c): logarithm of household expenditure on labour.
Dependent variable in (9d): household expenditure on labour in pesos of 2004

	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 R2	0.06	0.05	0.11	0.05
LR Chi2	16.35	13.90	26.49	25.58
Prob > chi2	0.022	0.053	0.000	0.000

Absolute value of t statistics in parentheses

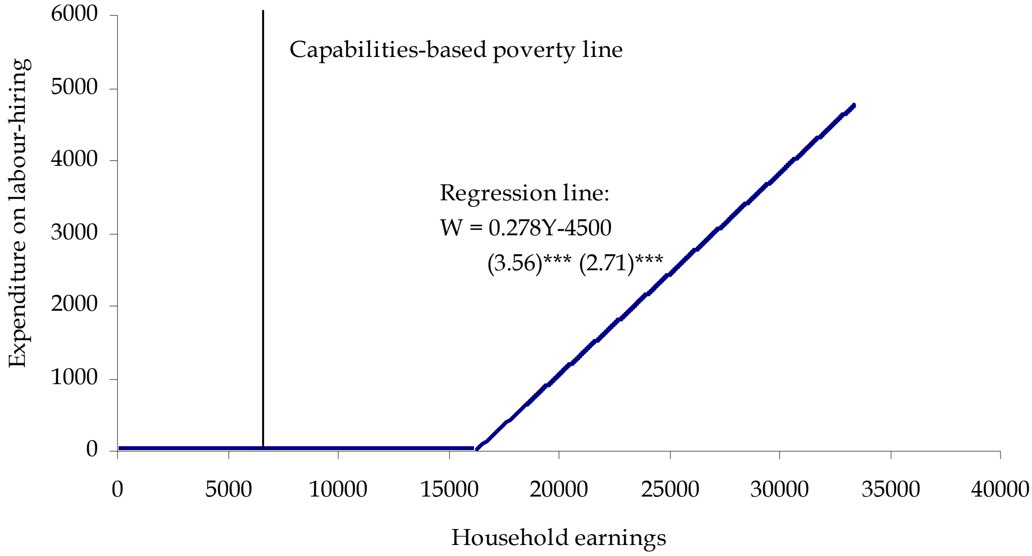
* significant at 10%; ** significant at 5%; *** significant at 1%

The empirical evidence show that a one percent increase in the amount of credit borrowed gives rise to a 2.6 percent in expenditure on labour hiring, and the results are statistically significant at 10 percent level; however, when the same equation was estimated with the length of membership as the impact variable (Equation 9b in Table 5), the slope coefficient became statistically insignificant, although its magnitude suggests that there might be a positive impact of the length of programme participation on labour hiring. Our results thus are inconclusive in attempting to confirm any direct impact of microcredit on labour-hiring. We infer that the statistical insignificance of M_i might reflect the small number of households in the sample that did actually hired labourers, although similar results have been reported elsewhere (see e.g. Mosley and Rock 2004).

We find, however, a large and significant elasticity of expenditure on labour-hiring with respect to household earnings. Other things held constant, a one percent increase in household earnings is predicted to give rise to a 5.8 percent increase in expenditure on labour hiring. Our results support the hypothesis of an indirect route through which microcredit could impact labour hiring: if by borrowing capital, enterprising households are able to boost their earnings, then an increasing probability of labour expenditure is observed. The large elasticity reported can be explained by the low wage rate paid to labourers relative to household earnings, reflecting the degree of welfare inequality in urban poverty Mexico. The results also suggest a downward effect of group lending on hires relative to individual lending, although the statistical insignificance cannot confirm this difference. Notice that most variables contained in the vector of household characteristics fail to report significant coefficients, a fact that might be reflecting the relative homogeneity among households participating in our study.

Although the computed elasticities reported in Table 5 provide valuable information about the relationship between household earnings and expenditure on labour, we still do not know at what level of earnings enterprising households begin to consider hiring labourers. The importance of identifying that minimum level is obvious: If labour-hiring emerges after households have achieved earnings above the poverty line, and if poverty targeting is widely adopted by microcredit programmes due to donor conditionality or organisational goals, the impact of microcredit on poverty through new hires could be prevented. 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 2 and in equation 9d, Table 5.

Figure 2. The relationship between household earnings and expenditure on labour-hiring (Figures in pesos of 2004)



Note that the slope coefficient ψ reports now the predicted values of an absolute change in household expenditure on labour-hiring conditional on an absolute change in earnings. As we hypothesized graphically in Figure 1, at low levels of household earnings, no household is willing to hire labourers for a relative high cost of buying efficiency units of labour, and therefore, self-employment remains dominant. Enterprising households will hire labourers only after reaching a minimum level of earnings, level at which households minimise the cost of efficiency units of labour. This level is graphically represented by $\bar{Y}$ in Figure 1. We envisage that level of household earnings as a platform for employment generation. Our estimations suggest that this platform is located in the context of urban Mexico, at about 16,250 pesos per month (around 1480 dollars). It is important to point out that 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, formal instruction, and public transport (see Sedesol

2002)[7]. After reaching that platform of earnings, the propensity of household expenditure on labour becomes positive and significant: a one-peso increase in the level of household earnings is predicted to give rise to 28 cents of labour expenditure, *ceteris paribus.*

It is apparent thus that at low levels of earnings, the cost of hiring units of efficiency labour is too high as an option for production, due to either productivity factors or informational asymmetries. In the context of Africa, Mosley and Rock (2004:477) 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 reveals that the vulnerable non-poor consider hiring labourers only after reaching the upper limit of labour supply (depicted at L^H in Figure 1), at the point where households have achieved a welfare status well above the poverty line. To illustrate this, take the following case:

Mr A. lives with his mother and two younger sisters in San Miguel Teotongo, to the Eastern area of Mexico City. He runs a small grocery in a neighbourhood located about 40 minutes from the place of residence. He is the only source of household income. As a competitive strategy, he offers a 24-hours service, 7 days a week, and in order to keep running the business throughout the night, he hires two labourers. He pays 850 pesos (some US $76) for 40 hours per week. This wage is about twice the capability-based poverty line derived for urban areas in Mexico. The monthly earnings reported by Mr A are in the order of US $1728, which correspond, after being weighted by equivalence factors as in Rothbarth (1943), to about 3.15 times the poverty line. When questioned about the reasons of hiring labourers, Mr. A replied: "*The business has been growing and I wanted to offer longer opening hours, but I cannot work 24 hours, you know. My sisters and my mother cannot help me either. It is too dangerous for them to work at nights. That is why I decided to hire my employees.*.."

Although we found no evidence of poor households hiring labourers, we did find that almost one-third of labourers hired by loan-supported (and non-poor) enterprising households were suffering from extreme deprivation, that is, with incomes below z_1 [8],

[7] This poverty line is estimated at 6570 pesos per month for an average household, which is the product of the *capability-based* poverty line derived at 1507.5 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.

whereas 60 percent of hires reported incomes below an asset-based poverty line (z_3[9]) that measures 'moderate' poverty in urban Mexico (see Sedesol 2002). Important differences were also identified between treatment and control groups in relation to the wage paid to poor labourers: taking the capability-based poverty line as reference, we observed that poor labourers 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 percent of the poverty line. In fact, we identified a significant association at the 0.05 percent level between treatment and control groups in relation to the units of labour hired. Labourers employed by treatment households worked on average 34 hours per week with reference to 20 hours reported from workers employed by control groups (see Table 6). It is apparent thus that by participating in a microcredit programme, non-poor enterprising households may increase their labour supply up to a level that ultimately benefits poor labourers. But although wage differences are associated to the intensity of labour, efficiency factors may also be driving up the wage rate. In the following section, we briefly discuss our findings.

[9] The asset-based poverty line is derived by adding to the food-based poverty line, a mean value of a non-food expenditure component, y following the Engel method. This threshold of 'moderate' poverty is set at 1881 pesos of 2004

Table 6. 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
Employers as proportion of total borrowers (%)	15.56	13.79
Labourers per employer (average)	1.5	1.3
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

Statistical association 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.

5.1 Labour intensity vs. labour efficiency

As household expenditure on labour is given by the product $L^h\lambda(w)$, where L^h is the number of units of labour hired, and $\lambda(w)$, the wage rate per unit of labour, conditional on efficiency factors, we can derive the elasticity coefficients of the wage rate, relative to the number of units of labour hired, $d(\ln w)/d(\ln L^h)$ [10], in order to estimate the relative change in labour efficiency among poor labourers. If the elasticity is greater than one, then efficiency factors may be driving up the wage rate. Our estimations report an elasticity equal to 1.19, with a slope coefficient significant at 1 percent level (*t*–statistic= 5.73, p= 0.00) , suggesting that non-poor enterprising households not only increase expenditure on labour as a result of higher labour intensity, but also due to efficiency factors. However, the proximity of the elasticity to the unity implies that such efficiency factors (if any) are rather modest. Nonetheless, due to data constraints, we were unable to explore this issue in more detail, leaving it as an area for future research.

6. Concluding remarks

Our study has provided insights into the dynamics involving credit markets and labour, with important implications for poverty policy. First, after controlling for endogeneity constraints, we find positive and significant impacts of microcredit on labour supply that are associated to the length of programme participation. This implies that not only credit access but also membership duration is an important determinant in an increased

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

allocation of labour resources, with implications for the welfare status of loan-supported enterprising households.

Second, an increased allocation of labour resources has also revealed indirect routes through which microcredit impact extreme poverty in urban settings: If by borrowing capital, enterprising households increase the levels of output to such extent that they cannot supply by themselves the required units of labour for production, then the marginal propensity to hiring labour becomes significant. We observed that behaviour only after households had crossed a minimum income threshold, at a level approximately three times as high as the poverty line. We envisage that income threshold as a platform for employment generation in the context of fragmented urban labour markets.

Third, we find significant differences between wages paid by treatment and control households. While labourers employed by control groups received wages well below the poverty line, labourers hired by treatment households reported wages above such a threshold. Two factors appear to explain wage differences. The first is associated with labour intensity: Labourers hired by treatment households report more hours at work vis-à-vis labourers hired by control groups. The second is associated to labour 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 delivery may actually miss out important trickle-down effects through labour markets that can benefit poor labourers. Thus, by flexibilising poverty targeting and extending the breadth of the targeting population to the vulnerable non-poor and non-poor, microcredit programmes could indirectly contribute to alleviate poverty in urban environments where labour often represent the only source of livelihoods to the extreme poor.

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