The impact of credit on income poverty in urban Mexico. An endogeneity-corrected estimation

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Abstract.

In recent years, an important number of impact studies have attempted to examine the effect of credit on income poverty; however, many of these studies have not paid sufficient attention to the problems of endogeneity and selection bias. The few exceptional cases have employed econometric techniques that work at the village level. The problem is that the concept of *village* is inappropriate in the urban context where a large percentage of microfinance organisations in the developing world actually operate. This paper presents an econometric approach which controls for endogeneity and self-selection using data from a quasi-experiment designed at the *household* level, and conducted in three *urban* settlements in the surroundings of the Metropolitan area of Mexico City. The paper provides an estimation of the impact of credit, employing different equivalence scales in order to measure the sensitivity of the poverty impact to the intra-household distribution of welfare. We find a link between poverty impacts and lending technology. Group-based lending programmes are more effective in reducing the poverty gap but in doing so, they achieve insignificant impacts on the poverty incidence. By contrast, individual lending programmes reported significant and small impacts at the upper limits of deprivation but insignificant impacts on the poverty gap.

JEL Classification: C24; C81; O16; O17; O18; O19
Keywords: endogeneity; selection bias; microfinance; credit; income poverty; impact analysis; Mexico.

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Introduction

The role of credit in the process of economic development and poverty reduction is an issue of ongoing debate. In the past, it was common for the state to intervene in those "strategic sectors" that had difficulty in accessing capital, assuming a *trickle-down* effect that would ultimately benefit the poor. In this spirit, many state-banking institutions, were established in many developing countries in the middle 1940s and early 1950s under quasi- Keynesian principles of financial repression designed to enhance investment (referred to by Vogel and Adams (1997) as the *direct credit paradigm*); but this approach has been heavily criticised by the Ohio School[1] for aggravating inefficiencies in the financial sector and deepening the problems of moral hazard and adverse selection.

Since the late 1970s and early 1980s, a set of innovations[2] known today as *microfinance* were developed by institutions such as the Bangladeshi Grameen Bank, the Unit Desa System of the Bank Rakyat in Indonesia and the Bolivian BancoSol that made possible for institutional lenders to reduce informational costs related to the screening, incentive and enforcement problems, and for the poor to access institutional financing. Although microfinance institutions have become the preferable subsidy-recipients seen as more effective channels to reach the poor, the hypothesis that they have impacts on poverty reduction has not been adequately tested in most of the cases, particularly in the urban context, with a few exceptions in rural credit markets, e.g. Hulme and Mosley (1996); Pitt and Khandker (1998a and 1998b), and Coleman (1999), see also the review by Morduch and Haley (2002).

This paper presents an econometric approach that control for the problems of

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[1] For an illustrating example, see Adams, Graham and von Pischke (1984).

[2] Materialised in the form of *inter alia*, banking technology, financial services or institutional arrangements. For a discussion on this issue see Larivière and Martin (1998).

endogeneity and self-selection using data from a quasi-experiment designed at the *household* level and in the urban context. Our methodology also allows the evaluation of potential differences between group lending and individual lending technology regarding poverty impacts, particularly when the cost of borrowing is included in the analysis. The paper is divided as follows: Section 1 briefly presents the research design and the selected case-study organisations before discussing, in section 2 the econometric estimation procedure. Section 3 examines the effects of programme participation on households' income whereas section 4 presents the findings regarding poverty impacts. Section 5 concludes.

1. Research design

In order to collect primary data, we designed a type of quasi-experiment that is often referred to as *a non-equivalent, post test-only quasi-experiment* (Campbell and Stanley 1966), in which two groups of households were interviewed: treatment and control. A major problem that emerges with the *non-equivalent, post test only quasi-experiment*, referred hereafter as simply *quasi-experiment*, is that the two groups, treatment and control, may differ in important ways that influence the decision of borrowing and thus, the outcome of interest. In other words, there might be unobservable factors related to e.g. individual efforts, abilities, preferences and attitudes towards risk that could affect the internal validity of the study.

In order to reduce potential selection problems, households who had self-selected to participate in a credit programme and had been accepted by the lender and therefore were actively participating in the credit programme were eligible to be sampled as *treatment group*. Participants with loans in arrears were also included in the group in order to strengthen the internal validity. Similarly, households who had self-selected to participate in a credit programme and had been accepted by the lender, but had not received a loan by the time the quasi-experiment was conducted, were eligible to be sampled as the *control group.* Additionally, we followed a *geographical criterion*, consisting in operationalising the quasi-experiment amongst households living in the same settlement, in areas with a minimum level of socio-economic and cultural homogeneity, in order to hold constant factors such as infrastructure, cost of inputs and local prices[3].

The quasi-experiment was conducted amongst 148 households living in three urban settlements in the surroundings of the Metropolitan area of Mexico City, where three case-study organisations operate: 1) Servicios Financieros Comunitarios (FINCOMUN); 2) Centro de Apoyo al Microempresario (CAME), and 3) Programas para la Mujer Mexico (PROMUJER). In this sense, we had tree locations, one for each case-study organisations.

1.1 The case-study organisations

The first case-study organisation is Fincomun. The organisation operates in San Miguel Teotongo, a neighbourhood with 80,000 inhabitants located in the Iztapalapa District, to the eastern periphery of Mexico City, one of poorest of the metropolitan area. Unlike most of the microfinance organisations in the country, Fincomun heavily relies on *individual lending*. By the end of 2004, after 10 years of operation, the organisation had almost 26 thousand borrowers (60% were women), with a loan portfolio of around 170 million pesos (17 million US dollars). The number of active borrowers, and the loan portfolio increased at an impressive rate of 302% and 256%, respectively in the period 1994-2004, where the portfolio at risk for more than 30 days was in the order of 4.98%.

The second organisation under study is CAME. It mainly operates in the Chalco Valley, one of the most densely populated municipalities in the country with about 324 thousand inhabitants. The Chalco Valley is located to the eastern

[3] For a copy of the instruments of data collection, contact me at: m.nino@sheffield.ac.uk

periphery of the Metropolitan area of Mexico City and remains as one of the poorest in the region. CAME began operations in 1993 employing the methodology of village banks. By the end of 2003, CAME had more than 40,000 active members, grouped in 1,600 income-generating groups or village banks. Women integrated 80% of these groups. Compulsory savings range from 10% to 12% depending on the loan size, and have grown at an annual average rate of 98% from 1995 to 2003, amounting more than 138 million pesos by the end of period. Deposits represented 2.38 times the loan portfolio that resulted in a loan-to-savings ratio of 42%.

Finally, the third organisation under examination is Promujer. This organisation mainly operates in Tula City and the surrounding areas in the State of Hidalgo, one of the poorest in the country. About 90,000 inhabitants live in Tula city, which is located at the centre of the country, two hours from Mexico City. Promujer employs the methodology of communal banks that combines group lending and training as the main services provided. In first quarter of 2004, the organisation reported 7,300 active borrowers with a loan portfolio that averaged 7.8 million pesos. Only women can participate in the credit programme, which reported a portfolio at risk for more than 30 days in the order of only 0.6%.

2. The econometric estimation procedure

To begin with, our exposition considers the case where household *i* decides to participate in a credit programme in order to finance any specific productive activity. The amount of capital supplied is exogenously determined by the lender *L*, who set up this maximum threshold according to level of participation in the programme. The lender is expected to exploit several screening, incentive and enforcement devices to deal with the problems of moral hazard and adverse selection that are related to borrowers' behaviour (Akerlof 1970; Besley and Coate 1995; Hoff and Stiglitz 1990). Some of these devices are, *inter alia*, progressive lending, compulsory savings schemes, periodical repayment schedules, and so on.

Given the particular environment in underdeveloped financial markets, the demand for credit is assumed to be rationed by the lender (Stiglitz and Weiss 1981), and endogenously determined by household characteristics such as the stock of human capital, individual preferences and attitude towards risks. Our primary concern is to estimate the effect of credit on the outcome to be investigated Y_i, which is observed through the income variable. We consider the following model:

$$Y_i = X_i\beta + I_i\delta + u_i \tag{1}$$

where X_i is a vector of exogenous households characteristics and I_i is a dichotomous variable with value $I = 1$ if household i is a programme participant, $I = 0$ otherwise. The model measures the impact of programme participation by the coefficient of the parameter estimate, δ. An important assumption here is that programme participation is *always* voluntary. The variable I_i cannot be treated as exogenous if we assume a potential problem of *selection bias*, i.e. if the decision of a household of whether or not to participate in the credit programme depends not only on the effort, abilities, preferences and attitudes towards risk that generate individual *self-selection,* what we refer to as a demand-related bias, but also on the *selectivity discrimination* made by credit programmes, referred here to as a supply-related bias)[4]. An illustrative example of the latter appears when credit officers at Fincomun screen out applicants with no previous business experience, or when village-bank's members at CAME, or solidarity groups at Promujer reject new applicants who do not live in the same neighbourhood. We consider, thus, a specification

[4] The problem of selectivity has been widely discussed in several fields, in particular the labour market [Heckman (1974, 1979); Cogan (1980); Lee (1978); Abowd and Farber (1982), among many others]; however, just recently it began to be addressed in the literature of microfinance. Some examples are Pitt and Khandker (1998a, 1998b) and Coleman (1999).

equation in the form:

$$Y_{1i} = \mathbf{X}_{1i}\beta_1 + \mathbf{I}_i\delta + u_{1i} \text{ (for programme participants)} \quad (2)$$

$$Y_{2i} = \mathbf{X}_{2i}\beta_2 + u_{2i} \text{ (for non participants)} \quad (3)$$

$$I_1^* = \mathbf{Z}_1\gamma_1 - \varepsilon_1 \quad (4)$$

$$I_2^* = \mathbf{Z}_2\gamma_2 - \varepsilon_2 \quad (5)$$

where $\mathbf{I}_i$ is defined by two components: I_1^* refers to the decision of a household of whether or not to participate in a credit programme, and I_2^* refers to the decision of the credit officer or group members of whether or not to accept such applicants. In this sense,

$I_1 = 1$ if household *i* chooses to participate in the credit programme

$I_1 = 0$, otherwise

$I_2 = 1$ if household *i* is accepted by group members or the credit officer

$I_2 = 0$, otherwise

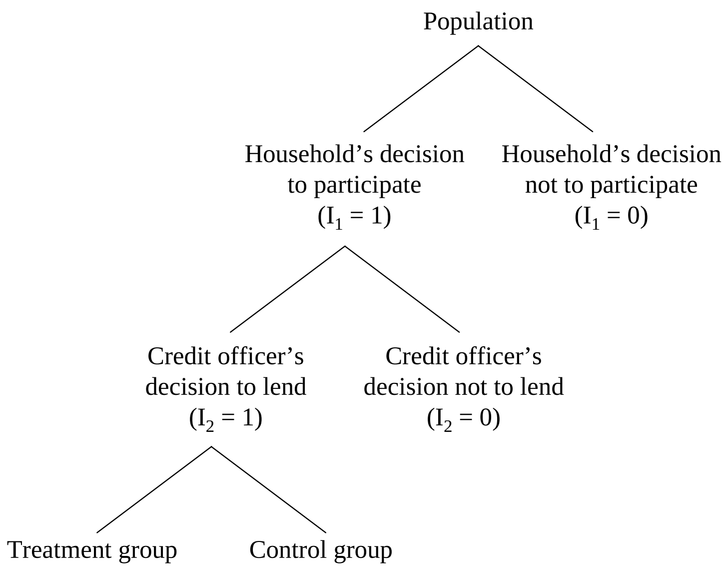

Figure 1. The decision process for programme selectivity. Adapted from Maddala (1999)

A problem emerges here when we cannot observe households who choose either to participate or not, *and* households who are either accepted or rejected by credit officers or group members, i.e. $I = I_1 + I_2$, but just as a single indicator $I = I_1 \cdot I_2$. As a result, what we observe is household i self-selecting to participate in the credit programme and being accepted by the lender. Thus, we can only specify the distribution of households who have been accepted to participate in the programme (I_2^*) and then estimate the parameter γ_2, if these households have previously self-selected ($I_1 = 1$). Our estimation strategy therefore will focus on households who have satisfied the condition $I = I_1 \cdot I_2$ (see figure 1).

Maddala (1999) suggests to define I_2^* over the whole population i.e. identify households with business activity or living in the same neighbourhood, and then analyse the model from the truncated sample where the parameters γ_1 and γ_2 can be estimated by maximising a likelihood function, e.g. Probit or Tobit. The argument is, Maddala states, that *in principle* I_2^* *exists even for the non-applicants* (1999:261). Thus, the observed Y_i can be defined as $Y_i = Y_{1i}$ if $\mathbf{I}_i = 1$, and $Y_i = Y_{2i}$ if $\mathbf{I}_i = 0$, where the participation decision function is given by $I_i^* = Z_i\gamma = \varepsilon_i$. In another paper, Maddala (1977) derives the covariance matrix as follows:

$$Cov(u_{1i}, u_{2i}, \varepsilon_i) = \begin{pmatrix} \sigma_{11} & \sigma_{12} & \sigma_{1\varepsilon} \\ \sigma_{12} & \sigma_{22} & \sigma_{2\varepsilon} \\ \sigma_{1\varepsilon} & \sigma_{2\varepsilon} & 1 \end{pmatrix} \qquad (6)$$

that enables us to evaluate the impact of programme participation on the outcome of interest, Y_i by comparing the expected outcome for treatment and control groups. Notice that both groups are participants with a time-variance difference that accounts for the length of membership. Consequently, control groups are integrated by households who just joined the credit programme. We follow the specification:

$$Y_{1i} = \mathbf{X}_i\beta_1 + u_{1i} \text{ (for treatment group)} \tag{7}$$

$$Y_{2i} = \mathbf{X}_i\beta_2 + u_{2i} \text{ (for control group)} \tag{8}$$

and

$$E\langle Y_{1i} | I_i = 1\rangle - E\langle Y_{2i} | I_i = 0\rangle = X_i(\beta_1 - \beta_2) + \sigma^* \frac{\phi(Z_i\gamma)}{\Phi(Z_i\gamma)} + V \tag{9}$$

where $\sigma^* = (\sigma_{2\varepsilon} - \sigma_{1\varepsilon})$; $\phi(\cdot)$ and $\Phi(\cdot)$ are the density of the distribution function and the cumulative distribution function of the standard normal, respectively, and $E(V) = 0$. Under self-selectivity, $\sigma^* > 0$, therefore equation (9) will report greater coefficients. In other words, households with comparative advantages will benefit more from the credit programme than disadvantaged households. However, since we surveyed households that satisfied the condition $I = I_1 \cdot I_2 > 0$, we believe to have considerably reduced the selection problem.

2.1 Using the Heckman procedure with I_i as endogenous regressor

Despite the fact that we believe that our sample strategy addresses the problem of self-selectivity, we may still encounter a problem of endogeneity in the model of programme participation if the explanatory variable I_i is correlated with unobservable factors that are relegated to the error term u_i. In other words, u_i may contain an omitted variable that is uncorrelated with all explanatory variables except I_i. In order to control for the potential endogeneity problem we follow a *Heckit* estimation procedure (Heckman 1979) with an identifying instrumental variable (IV)[5]. This Maximum Likelihood method follows the model:

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

$$Y_i = X_i\beta_y + I_i\delta + u_i^y \quad (10)$$

$$I_i = X_i\beta_I + Z_i\gamma + u_i^I \quad (11)$$

where X_i is a 1 x K vector of household characteristics that capture not only conventional variables such as age, sex, and the dependency ratio, but also elements related to the stock of household capitals such as years of formal education (human capital); housing ownership and the state of the property (physical capital); and the number of household members at work and the number of years in business as proxy variables for the characteristics of the labour market. We introduce an exogenous regressor Z_i in equation (11) as the identifying instrument that will not be included in equation (10). Z_i is an observable variable distinct from those in X_i that affect I_i but not the outcome of interest Y_i conditional on I_i. In other words, the instrument must be *partially* correlated with I_i, i.e. the coefficient on Z_i must be nonzero, $\gamma \neq 0$, so $Cov(Z_i, u_i^I) \neq 0$, whilst Z_i must be uncorrelated with Y_i, so $Cov(Z_i, u_i^y) = 0$, where the projected error, $\mathrm{E}(u_i^y) = 0$ is uncorrelated with Z_i. Selecting an appropriate instrument becomes a crucial, but also a complex, task for our estimation.

The Heckit procedure allows us to test for the assumption of no self-selectivity by estimating the inverse Mills ratio, $\lambda(\cdot) \equiv \dfrac{\phi(\cdot)}{\Phi(\cdot)}$, resulting from the relationship between the density of the distribution function, $\phi(\cdot)$, and the cumulative distribution function of the standard normal, $\Phi(\cdot)$ in equation (11). As suggested by Heckman (1979), we can estimate consistently the parameters β_I and γ by exploiting the properties of the first stage Probit estimation and then get the estimated inverse Mills ratio, $\hat{\lambda}$. In the second stage we obtain the parameters β_y and δ from Ordinary Least Squares (OLS) with the inverse Mills ratio added to the regressors as follows:

$$Y_i = X_i\beta_y + L_i\theta_y + I_i\delta + \lambda M + u_i^y \quad (12)$$

where we have also included L_i that is a 1 x K vector of financial market characteristics which captures the effect of formal and informal financial agents such as banks, moneylenders and rotating savings and credit associations (ROSCAS) that compete in the market with microfinance organisations**.** The rationale behind incorporating these variables into L_i rely on the assumption that if we do not control for the effect of other intermediaries on the outcome of interest Y_i, then the parameter δ that captures the effect of programme participation may be inconsistent, i.e. we could wrongly attribute some outcomes to microfinance organisations when in fact they come from for example, ROSCAS.

The two-stage Least Square (2SLS) procedure yields consistent estimates in the parameter of interest δ (Wooldridge 2002) where M and λ are the inverse Mills ratio and its parameter estimate, respectively. A simple way of testing for self-selectivity is under the null hypothesis of no selection bias, $H_0 : \lambda = 0$, using the usual 2SLS t statistic. When $\lambda \neq 0$ we may have a problem of self-selectivity.

2.2 Selecting the instrumental variable

In order to select the instrumental variable, we analysed instruments used by other researchers. Pitt and Khandker (1998a), for example, have exploited a particular exogenous rule that organisations such as Grameen Bank and BRAC in Bangladesh have set up in order to restrict programme participation to non-poor households. This exogenous rule is related to land-ownership, and has been defined as *households owning more than half an acre of land*. However, in the context of urban Mexico, this instrument would be inappropriate:

Firstly, microfinance organisations in Mexico do not impose any asset-specific restriction for programme participation. Secondly, unlike the context of rural Bangladesh, agricultural activities in the surroundings of Mexico City are non-existent. Thirdly, land-ownership is not a reliable indicator of well-being in the urban context. Finally, the technique of maximum likelihood estimation followed by Pitt and Khandker was designed to use village fixed effects[6]; however, the concept of *village* is in itself inappropriate in the urban context, where poor settlements are highly populated.

Given the presence of credit rationing in the market, it is reasonable to assume that the level of programme participation, I_i, is exogenously determined by the lender, i.e. microfinance organisations require a set of minimum requirements to participate in the programme. Thus, we decided to concentrate on the supply side in order to identify the instrument Z_i.

In the beginning we considered an observable variable with computational values that varied from household to household and which reflected the heterogeneity of the cost of borrowing. We computed this variable by estimating the cost of transportation per credit cycle C_i^T, in which we capture the physical and geographical characteristics of the accessibility to the branch, in addition to the opportunity cost of borrowing C_i^O, as a proxy of the income forgone for attending weekly meetings and other activities.

We transformed this variable into logarithmic form, in order to test for the underlined assumptions of no correlation between the identifying instrument and the income variable as follows:

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[6] The authors used a weighted exogenous sampling maximum likelihood-limited information maximum likelihood-fixed effects (WESML-LIML-FE) approach.

LGINCOMEPC = β_1 AVEDU$_i$ + β_2 HOWNER$_i$ + β_3 HESTATE$_i$ + β_4 TIMEBUS$_i$ + β_5 WWORKER$_i$ + β_6 DEPENDRATIO$_i$ + β_7 AGE$_i$ + β_8 WOMAN$_i$ + β_7 MARITAL$_i$ + θ_1 ROSCAS$_i$ + θ_2 FORMALCREDIT$_i$ + θ_3 MONEYLENDER$_i$ + δ LGMAXCREDIT$_i$ + γ LGCOSTBORROWPC$_i$

We found that, in the case of Fincomun, the coefficient γ of LGCOSTBORROWPC rejected the null $H_0 : \gamma = 0$ at 5% level of significance (see table 1), throwing out any possibility of using this variable as the identifying instrument in the impact estimation for the three institutions participants in the study as a whole[7]. However, this variable gives us important information regarding the elasticity of demand for credit in relation to the cost of borrowing. For example, a one percent change in the cost of borrowing gives rise to a 1.574 percent change in the amount of credit demanded from borrowers at Fincomun, *ceteris paribus*, and this elasticity was in the order of 1.705 and 1.458 for participants at CAME and Promujer, respectively.

Table 1.Identifying equations on functional form
Logarithm of the cost of borrowing (LGCOSTBORROWPC) as identifying instrument
Dependent variable in (11): logarithm of the maximum amount of credit borrowed (LGMAXCREDIT)
Dependent variable in (12): logarithm of monthly income per adult equivalent 1 in pesos of 2004 (LGINCOMEPC)

	FINCOMUN		CAME		PROMUJER	
	Eq. 11	Eq. 12	Eq. 11	Eq. 12	Eq. 11	Eq. 12
LGCOSTBORROWPC	1.574	0.325	1.705	0.082	1.458	0.055
	(21.18)***	(2.05)**	(10.74)***	(0.62)	(14.61)***	(0.50)
Observations	55	55	46	46	47	47
R-squared		0.44		0.49		0.41

Absolute value of t statistics in parentheses

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

We found that these elasticities are correlated with the level of households' earnings. This is simply because those households with better business opportunities and higher expected returns also absorb a higher opportunity cost of borrowing, particularly when screening and enforcement devices such as periodical repayment schedules, exploited by group lending programmes,

[7] We tested the $\gamma \neq 0$ condition in (11) and (12) by computing a heteroskedasticity-robust t statistic after OLS estimation.

are very time-intensive.

The problem is that in fragmented credit markets, where the immediate option is the moneylender, borrowers may decide to remain in the programme in order to take advantage of progressive lending and borrow the maximum amount of capital available in order to minimise these costs. This behaviour may continue as long as the percentage change in the loan size is larger than the percentage change in earnings, i.e. progressive lending is available, and the credit market remains monopolistically concentrated. We discuss this issue regarding poverty impacts in sections 4 and 5.

In order to derive the identifying instrument, we tried to exploit the first component of LGCOSTBORROWPC, i.e. the logarithm of the cost of transportation per credit cycle, $\log C_i^T$, (referred here as LGCOSTRANSPC). Our argument here relies on the idea that there is a correlation between programme participation and accessibility to the branch but we do not see how this instrument may affect the income variable. We assume that the correlation between $\log C_i^T$ and I_i emerges from two sources:

First, microfinance organisations may decide to set up lending restrictions to households *living* a considerable distance from the branch due to the transaction costs implicitly related to the monitoring and enforcement processes. Regarding this particular issue, the Managing Director of Fincomun stated in an interview that a fundamental criterion for the organisation was to operate in a geographical radius that did not exceed a journey of 30 minutes walking or by public transport from the branch to the house of the applicant[8].

Second, we should expect, as mentioned earlier, a process involving individual

[8] In fact, this policy appeared to be a common practice amongst MFIs in Mexico. For example, the mean value for a time-dimensional variable that measured the distance from the household's residence to the branch was 20 minutes for the case of Fincomun (only outward journey); 21 minutes for CAME and 25 minutes for Promujer.

choice where households reporting high transaction and opportunity costs of participation would either have high incentives to borrow the largest amount of capital accessible in order to compensate these costs or may simply decide drop out or not to participate in the first place.

Our survey collected information on the cost of transportation per week given the periodicity of the group meetings; however there were a substantial number of missing values in the dataset that reflected the individual choice of walking to the branches rather than using public transport (see table 2). Since several programme participants walk to attend periodical meetings, we decided to explore the attributes of the time dimension that captured the information about the distance from the residence (or businesses) of the programme participant to the branch, as a proxy of *accessibility*, in substitution of $\log C_i^T$.

Table 2 Cost of transportation per credit cycle

	Figures in pesos of 2004				
	Sample	Mean	Maximum	Minimum	Missing values
FINCOMUN	55	99.78	1280	0	39
CAME	46	29.91	320	0	39
PROMUJER	47	60.60	320	0	32
Pooled sample	148	65.62	1280	0	110

Our survey collected information on the time (in minutes) that participants spent since they left home (or business) until they arrived at the branch. This variable was weighted when public transport was used in order to add the time that they would have consumed if they had walked to the branch. We coded this identifying instrument as DISTANCE.

Table 3. DISTANCE as identifying instrument
Dependent variable in (11): logarithm of maximum amount of credit borrowed (LGMAXCREDIT)†
Dependent variable in (12): logarithm of monthly income per capita in pesos of 2004 (LGINCOMEPC)

	FINCOMUN		CAME		PROMUJER	
	Eq. (11)	Eq. (12)	Eq. (11)	Eq. (12)	Eq. (11)	Eq. (12)
DISTANCE	0.028	-0.000	0.073	0.005	0.066	-0.005
	(1.88)**	(0.09)	(2.15)**	(0.94)	(1.92)*	(1.57)

Absolute value of t statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%
† The Heckman procedure transforms LGMAXCREDIT into a dummy variable for treatment group = 1 if I_i > 0.

When we estimated the reduced form equation (11) with DISTANCE as identifying instrument $\mathbf{Z}_i$ for each of the microfinance organisations, the p-values of the *t* statistic for the coefficient γ rejected the null of $H_0 : \gamma = 0$, i.e. it reflected the statistically significance correlation between accessibility and participation; however, when we included $\mathbf{Z}_i$ in equation (12), the parameter estimate γ accepted the null of no correlation against the outcome of interest Y_i (see table 3). As a result we were able to use DISTANCE as the identifying instrument for the Heckit procedure.

One of the reasons for choosing the Heckit procedure is due to its structural qualities. On the one hand, it enables us to test for the assumption of no self-selectivity by exploiting the non-linearity properties of the inverse Mills ratio (coded in the regression equation as MILLS). As discussed above, we conducted the quasi-experiment in a way to reduce the problem of self-selectivity; however, we needed to test the hypothesis of no selection problem. The results accepted the null of no self-selectivity, confirming that we followed an appropriate methodological procedure during the data collection.

Table 4 Robustness of DISTANCE as instrumental variable
Endogenous explanatory variable in (12): Logarithm of the maximum amount of credit borrowed (LGMAXCREDIT)†
Dependent variable in (12): logarithm of monthly income per capita (LGINCOMEPC)

	FINCOMUN		CAME		PROMUJER	
	Equation (12) on functional form	Equation (12) with DISTANCE as instrument	Equation (12) on functional form	Equation (12) with DISTANCE as instrument	Equation (12) on function al form	Equation (12) with DISTANCE as instrument
LGMAXCREDIT	0.591	0.595	0.103	0.088	0.629	0.582
	(2.48)**	(3.39)***	(0.59)	(0.90)	(1.98)**	(1.88)*
MILLS	0.258	0.653	0.089	0.043	-0.053	0.261
	(0.58)	(1.57)	(0.67)	(0.15)	(0.14)	(1.05)
DISTANCE	0.002		0.006		-0.006	
	(0.32)		(1.13)		(1.06)	

Absolute value of z statistics in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%
† The Heckman procedure transforms the LGMAXCREDIT variable into a dummy variable for treatment group = 1 if Ii > 0

On the other hand, the Heckit procedure allows us to test for the quality of the identification variable, and provides us with important information about the robustness of the estimation. In order to do so, the identifying instrument DISTANCE was included in (12) alongside with the other exogenous variables, including the inverse Mills ratio. The identification is achieved by exploiting the properties of the inverse Mills ratio that result from the non-linear relationship of the exogenous variables in the reduced form equation (11). The coefficients and significance levels of LGMAXCREDIT and MILLS are reported in Table 4. After running the identification equation, the coefficients of the endogenous explanatory variable in the estimation equations as well as the Mills ratio for each organisation under study remained stable. The consistency of the results confirms the robustness of DISTANCE as the instrumental variable in our estimation.

3. Results from the second-stage Heckit estimation: the impact of programme participation on households income

We now turn to the results from the estimation of the impact of programme participation on households' income presented in table 6. We have estimated Y_i in (12) by employing the logarithm of income per capita and three different definitions of income per adult equivalent as the dependent variable. The use of adult equivalence scales is generally justified given the fact that children normally have lower consumption expenditure than adults and therefore they should be given a lesser weight. Some studies (e.g. Drèze and Srinivasan 1997) suggest that additional adults should be weighted less than the first adult after taking into account economies of scale.

Poverty rates can be sensitive to equivalence scales and thus, alter the conclusions reached on the impact of microfinance on poverty reduction. In this sense, it becomes important to look at this particular issue. There have been recent attempts to attach weights to the distribution of wealth in developing countries by assigning adult equivalencies to household members according to their age and sex [e.g. May, Carter and Posel (1995) in South Africa and Hentschel and Lanjouw (1995) in Ecuador]; however, given the lack of a general consensus regarding the use of equivalence factors in the context of Mexico, we decided to follow the approach adopted by Rothbarth (1943).

The equivalence factor takes the form $e_h = (A_h + \Phi K_h)^{\theta}$, where e_h is the equivalence factor for household *h*, A_h is the number of adults (from age 18 to 65) and K_h is the number of children in household *h*. The parameter θ is equal to 1 and Φ has different values corresponding to the age and sex of every child. In this sense, boys in the range 0-5 years have a Φ value of 0.661 while girls have one of 0.609; boys in the range of 6 to 12 years have a parameter Φ of 0.750 while girls have one of 0.664; young men in the range of 13 to 18 years have a parameter of 0.633 while young women in the same range of age have a weight of 0.635. Finally elderly men and women (65 years of age and older) were assigned values of 0.553 and 0.570, respectively. For the purpose of our analysis, we will refer to this measurement as equivalence factor 1 (IAE1).

We also include in our estimations other equivalence factors in order to conduct a sensitivity analysis. We follow, therefore, the adult equivalence scales developed by Wagstaff and van Doorslaer (1998) where it is given the parameters Φ and θ a value equal to 0.75 and children are defined as those aged less than 14 years. We refer to this measurement as equivalent factor 2 (IAE2). Additionally we employ the OECD modified equivalence scale based on Hagenarrs *et al*, (1998) which weights the first adult with 1, additional adults with 0.5 and children aged 14 and less with a weight of 0.3. In our analysis we refer to this product as the income per adult equivalent 3 (IAE3). For comparative purposes, we have also included income *per capita* as another proxy of distribution of household wealth.

As we were expecting, after taking into account distributional factors, the level of individual welfare was affected by equivalent factors, with income per capita being the measurement that most over-stated the level of deprivation (see table 5). For analytical purposes, we focus on the income per adult equivalent 1.

Note that the coefficient of the inverse Mills ratio revealed no evidence of selection bias (see table 4 in section 2.2), allowing us to concentrate on the OLS estimation. If we had encountered endogeneity problems, we should have focused on the Heckit estimation. The econometric results of the impact of programme participation on income are shown in table 6. The parameter estimate δ of the impact variable, I_i, reports the difference in the *mean* log income per adult equivalent of treatment households relative to the control group. The slope coefficients show, as expected, a positive sign for each of the three credit programmes; however, the coefficients were only statistically significant different from zero in the case of Fincomun.

Table 5. Intra-household distribution of income by equivalent factors

Figures in pesos of 2004	FINCOMUN		CAME		PROMUJER	
	Treatment	Control	Treatment	Control	Treatment	Control
Average household IC per month	9,899	4,831	6,567	5,219	6,339	6,663
Household income as a % of treatment group	100%	49%	100%	79%	100%	105%
Average monthly IC	2,338	1,372	1,707	1,473	1,711	1,503
IC as a % of treatment group	100%	59%	100%	86%	100%	88%
Average monthly IAE1 a/	2,684	1,533	1,963	1,699	2,010	1,766
IAE1 as a % of treatment group	100%	57%	100%	87%	100%	88%
Average monthly IAE2 b/	3,545	1,945	2,524	2,106	2,546	2,364
IAE2 as a % of treatment group	100%	55%	100%	83%	100%	93%
Average monthly IAE3 c/	4,208	2,271	2,982	2,474	3,040	2,836
IAE3 as a % of treatment group	100%	54%	100%	83%	100%	93%

a/ Income per adult equivalent 1 follows the approach developed by Rothbarth (1943),

B/ Income per adult equivalent 2 follows Wagstaff and van Doorslaer (1998).

c/ Income per adult equivalent 3 follows the OECD modified equivalence scale based on Hagenarrs et. al, (1998).

In order to calculate the percentage change of income per adult equivalent of treatment households relative to the control group, we took the antilog of the parameter estimate I_i and computed $(e^{\delta}-1)\times 100$ (Halvorsen and Palmquist 1980).

Table 6. The impact of programme participation on households' income

Endogenous explanatory variable (I_i in Equation 12): Logarithm of the maximum amount of credit borrowed (LGMAXCREDIT) †

		FINCOMUN		CAME		PROMUJER		Pooled sample	
		OLS	Heckit	OLS	Heckit	OLS	Heckit	OLS	Heckit
Dependent variable (Y_i in Equation 12): logarithm of monthly income per capita in pesos of 2004 (LGINCOMEPC)	LGMAXCREDIT	0.553	0.595	0.126	0.088	0.110	0.582	0.313	0.115
		(2.53)**	(3.39)***	(0.81)	(0.90)	(0.73)	(1.88)*	(3.52)***	(1.75)*
	MILLS		0.653		0.043		0.261		0.129
			(1.57)		(0.15)		(1.05)		(0.61)
Dependent variable (Y_i in Equation 12): logarithm of monthly income per adult equivalent 1 in pesos of 2004 (LGINCOMEPAE1) a/	LGMAXCREDIT	0.548	0.588	0.140	0.099	0.102	0.701	0.315	0.121
		(2.57)**	(3.27)***	(0.91)	(1.00)	(0.67)	(2.33)**	(3.59)***	(1.81)*
	MILLS		0.671		-0.010		0.293		0.118
			(1.57)		(0.03)		(1.18)		(0.08)
Dependent variable (Y_i in Equation 12): logarithm of monthly income per adult equivalent 2 in pesos of 2004 (LGINCOMEPAE2) b/	LGMAXCREDIT	0.605	0.554	0.109	0.063	0.067	0.691	0.314	0.111
		(2.91)***	(3.05)***	(0.80)	(0.68)	(0.44)	(2.53)**	(3.75)***	(1.74)*
	MILLS		0.676		0.183		0.294		0.226
			(1.57)		(0.65)		(1.28)		(1.09)
Dependent variable (Y_i in Equation 12): logarithm of monthly income per adult equivalent 3 in pesos of 2004 (LGINCOMEPAE3) c/	LGMAXCREDIT	0.611	0.558	0.095	0.066	0.065	0.737	0.313	0.109
		(2.93)***	(3.14)***	(0.71)	(0.70)	(0.43)	(2.75)***	(3.74)***	(1.69)*
	MILLS		0.661		0.180		0.311		0.219
			(1.57)		(0.63)		(1.35)		(1.05)

Robust t statistics in parentheses

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

† The Heckman procedure transforms LGMAXCREDIT into a dummy variable for treatment group = 1 if $I_i > 0$

a/ Income per adult equivalent 1 follows the approach developed by Rothbarth (1943), and it has been used by the Mexican government to identify poverty lines at national level.

b/ Income per adult equivalent 2 follows the approach developed by Wagstaff and van Doorslaer (1998).

c/ Income per adult equivalent 3 follows the OECD modified equivalence scale based on the work of Hagenarrs *et. al* (1998).

For example, if we estimate the antilog of δ when the logarithm of monthly income per adult equivalent 1 was derived as the dependent variable we obtain $e^{0.548} = 1.7297$, suggesting that *ceteris paribus*, the *median* income per adult equivalent of treatment households with at least one year of programme participation at Fincomun was higher than that of the control groups by about 73%.

We observed nevertheless a degree of variability in the coefficient of I_i when different definitions of income per adult equivalent were introduced, suggesting that the impact analysis of microfinance might be sensitive to intra-household distribution of welfare. Surprisingly, the parameter estimate δ in the regression equation was positive *but* not significantly different from zero in the case of CAME and Promujer. In other words, although we were expecting a positive effect of programme participation on the level of individual welfare, there was no evidence to confirm this relationship. The starting point in examining the reasons of the insignificant levels of δ was to see the degree to which it might be related to the severity of deprivation amongst households' participants.

In fact, some researchers have found that very poor borrowers are more likely to report low income impacts not only because they are engaged in low-return self-employment activities (Hulme and Mosley 1996; Husain 1998; Zaman 1998; Wood and Shariff 1997)[9], but also because the process of decision making under uncertainty is driven by risk-averse behaviour, particularly at low levels of income (Ravallion 1988; Sinha and Lipton 1999). The problem is that the estimation procedure provides us with information on the impact of programme participation at the *mean* of the dependent variable; however, it does not tell us to what extent those participants are actually poor. Furthermore, notice that the parameter δ measures the *average* impact of

[9] Self-employment represented 85%, 65% and 71% of the income sources, for treatment households at Fincomun, CAME and Promujer, respectively.

programme participation on Y_i; however, it does not take into consideration the effect of borrowing over time.

Treatment households with say five years of membership are expected to report a greater impact than those households with just one or two years of membership. This is in part due to the effect of progressive lending that continuously increases the credit limit of borrowers. In order to address the latter issue we extend the Heckman procedure to a Tobit selection equation in section 3.1, before we concentrate in section 4 on examining the impacts on poverty reduction.

3.1 Substituting the *Heckit* procedure for a *Tobit selection equation*: the impact of borrowing on households' income

We replaced the treatment dichotomous variable I_i in equation (11) by a continuous variable, C_i, that measures the maximum amount of credit borrowed during the last credit cycle. We assume that C_i is *exogenously* determined by the lender *L,* who defines this maximum threshold according to level of participation in the programme. Thus we have the following specification equation

$$C_i^* = X_i\beta_c + Z_i\gamma + u_i^c \quad (13)$$

where

$$C_i = \max(0, C_i^*) \text{, i.e.} \quad (14)$$

$$C_i = C_i^* \quad \text{if} \quad C_i^* > 0 \text{ (for treatment group)} \quad (15)$$

$$C_i = 0 \quad \text{if} \quad C_i^* \leq 0 \text{ (for control group)} \quad (16)$$

and

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

Consequently, C_i takes a maximum value and a lower threshold zero in the form of a censored Tobit model (Tobin 1958) with a $C_i > 0$ for treatment groups and $C_i = 0$ for control groups[10]. In this way we believe to be capturing a more precise measure of the impact of programme participation by using C_i in the reduced form equation, where δ now measures the impact of credit *per additional unit of capital borrowed*. Notice that the use of OLS for the sub-sample for which $C_i > 0$ will produce inconsistent estimators of β_c and γ, since we are using only the data on uncensored observations (Wooldridge 2002), causing a downward bias result (Greene 2003)[11]. Thus, the Tobit model implies that the probability of observing $C_i > 0$ and $C_i = 0$ are $\phi(\cdot)$ and $p(C_i^* < 0) = \Phi(0)$, respectively, where $\phi(\cdot)$ and $\Phi(\cdot)$ denote the same density function and the cumulative density function of the standard normal analysed above in section 2. These assumptions are very similar to those implied in the probit selection equation, but now the log-likelihood function takes the form

$$\ln L = \sum_{C_i > 0} \left(-\ln \sigma + \ln \phi \left(\frac{C_i - X_i \beta_c}{\sigma} \right) \right) + \sum_{C_i = 0} \ln \left(1 - \Phi \left(\frac{X_i \beta_c}{\sigma} \right) \right) \tag{17}$$

which generates three conditional mean functions[12]: one of the latent variable C_i^*, which can be used to understand the *unobservable* factors (e.g. individual preferences, attitudes towards risk or entrepreneurship) that affect the propensity to borrow from microfinance organisations; one of the *observed* dependent variable C_i, which can be used to understand the determinants of the level of borrowing by treatment and control groups alike; and one of the uncensored observed dependent variable $C_i | C_i > 0$, which can be used to

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

[11] Goldberger (1972) and Greene (1981) have proved that the ratio of the OLS estimates to the maximum likelihood estimates get close to the proportion of data uncensored.

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

understand the determinants of the level of borrowing by treatment households alone.

We are particularly interested in looking at the conditional mean function of the observed dependent variable C_i that is *censored at zero* for control groups, and have disturbances normally distributed. In other words, we are interested in examining the *observed* factors that affect the level of household borrowing between treatment and control groups.

We can estimate now a credit function for the level of programme participation, which is determined by the marginal effects of the independent variables on the maximum amount of capital borrowed during the last credit cycle, C_i as follows:

$$C_i = \alpha_c + X_i \beta_c + Z_i \gamma + L_i \theta_c + u_i^c \qquad (18)$$

where X_i is a 1 x K vector of household characteristics; Z_i is a set of observable variables distinct from those in X_i that affect C_i but not the outcome of interest Y_i conditional on C_i that plays the role of the identifying instruments; L_i is a vector of financial market characteristics; α_c, β_c, γ and θ_c are the intercept and the unknown parameters, respectively whereas u_i^c is the error term that captures unmeasured household characteristics that determine borrowing levels.

The function for the outcome of interest Y_i, i.e. income per adult equivalent, conditional on the level of programme participation C_i takes the form

$$Y_i = \alpha_y + X_i \beta_y + L_i \theta_y + C_i \delta + u_i^y \qquad (19)$$

where α_y, β_y, θ_y and δ are the intercept and the unknown parameters respectively, whilst u_i^y is the error term reflecting unmeasured determinants of Y_i that vary from household to household. Given that we are including C_i as the explanatory variable in (23), we may expect some level of endogeneity emerging now from the lenders' policy-specifics that affect the *upper limit* of credit available and not only the *accessibility* to it, as discussed earlier when the Heckman procedure was estimated.

To select an identifying instrument for the Tobit selection equation, additional to DISTANCE, becomes once again an essential and difficult task. This instrument must satisfy the same conditions as in section 2 to enable us to estimate a 2SLS Tobit procedure, the type of method that Amemiya (1984) has referred to as Type III Tobit model. We derive this estimation equation as follows:

$$Y_i = \alpha_y + X_i\beta_y + L_i\theta_y + C_i\delta + R_i\upsilon + e_i \qquad (20)$$

where R_i and υ are the predicted Tobit residuals and its parameter estimate, respectively, and $e_i \equiv u_i^y - E(u_i^y | R_i)$, where (e_i, R_i) are assumed to be independent of X_i, i.e. $E(e_i | X_i, R_i) = 0$. The predicted residuals from the Tobit equation are estimated when $C_i > 0$ in (22) and then included as another regressor in (24) to yield consistent and efficient estimators (Wooldridge 2003). The null of no selection bias is tested in similar fashion as the Heckit procedure; however, we now use the 2SLS heteroskedasticity-robust t statistic on the predicted residuals: when $\upsilon \neq 0$ we encounter a selection problem.

In order to identify the additional instrument contained in Z_i, we explored the incentive devices employed by the case-study organisations that could affect C_i but not the outcome of interest Y_i. The selected identifying instrument was the length of membership, computed as the number of years of programme participation and coded as MEMBERSHIP. This variable was assumed to be related to progressive lending, an incentive device exploited by microfinance organisations to deal with the problem of moral hazard and reduce operational costs in the long run.

Table 7. Identifying instruments for the Tobit selection equation
Dependent variable in (22): logarithm of the maximum amount of credit borrowed (LGMAXCREDIT)
Dependent variable in (23): logarithm of monthly income per adult equivalent 1 in pesos of 2004 (LGINCOMEPAE1)

	FINCOMUN		CAME		PROMUJER	
	Eq. (22)	Eq. (23)	Eq. (22)	Eq. (23)	Eq. (22)	Eq. (23)
MEMBERSHIP	2.235	-0.024	2.074	0.018	5.487	-0.003
	(6.80)***	(0.19)	(6.78)***	(0.29)	(10.36)***	(1.22)
DISTANCE	0.060	-0.001	0.058	0.004	0.042	0.340
	(2.60)**	(0.41)	(1.76)*	(0.88)	(2.84)***	(1.65)

Absolute value of t statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

When we estimated equation (22) with DISTANCE and MEMBERSHIP as the identifying instruments contained in vector Z_i, the p-values of the *t* statistic for the coefficient γ for each of the case-study organisations rejected the null of $H_0 : \gamma = 0$, i.e. it reflected the statistically significance correlation between the maximum level borrowing, C_i and the two instruments contained in Z_i; however, when we included Z_i in equation (23), the parameter estimate γ accepted the null of no correlation against the outcome of interest Y_i (see table 7). We also followed Klein's rule of thumb (1961) to test the instruments for potential problems of collinearity. None of the auxiliary regressions with DISTANCE and MEMBERSHIP as dependent variables reported a higher R^2 than the one obtained from the main regression equation (22), rejecting any serious problem of collinearity. As a result we were able to use DISTANCE and MEMBERSHIP as identifying instruments for the Tobit selection procedure. The econometric results of the impact of credit on individual income using equivalent factors are shown below in table 8.

Table 8 The impact of borrowing on households' income

Endogenous explanatory variable (C_i in Equation 20): Logarithm of the maximum amount of credit borrowed (LGMAXCREDIT)

		FINCOMUN		CAME		PROMUJER		Pooled sample	
		OLS	2S-Tobit	OLS	2S-Tobit	OLS	2S-Tobit	OLS	2S-Tobit
Dependent variable (Y_i in Equation 21): logarithm of monthly income per capita in pesos of 2004 (LGINCOMEPC)	LGMAXCREDIT	0.065	0.070	0.014	0.003	0.015	-0.043	0.037	0.044
		(2.82)***	(1.41)	(0.80)	(0.09)	(0.83)	(0.94)	(3.67)***	(2.38)**
	RESID		-0.007		0.012		0.048		-0.008
			(0.12)		(0.41)		(1.30)		(0.42)
Dependent variable (Y_i in Equation 21): logarithm of monthly income per adult equivalent 1 in pesos of 2004 (LGINCOMEPAE1) a/	LGMAXCREDIT	0.064	0.075	0.015	0.003	0.015	-0.049	0.036	0.045
		(2.88)***	(1.57)	(0.89)	(0.07)	(0.79)	(1.12)	(3.77)***	(2.51)**
	RESID		-0.014		0.014		0.052		-0.010
			(0.25)		(0.47)		(1.46)		(0.52)
Dependent variable (Y_i in Equation 21): logarithm of monthly income per adult equivalent 2 in pesos of 2004 (LGINCOMEPAE2) b/	LGMAXCREDIT	0.070	0.085	0.012	0.004	0.010	-0.045	0.037	0.050
		(3.21)***	(1.96)*	(0.77)	(0.14)	(0.56)	(1.03)	(3.91)***	(2.87)***
	RESID		-0.019		0.008		0.045		-0.016
			(0.39)		(0.28)		(1.28)		(0.89)
Dependent variable (Y_i in Equation 21): logarithm of monthly income per adult equivalent 3 in pesos of 2004 (LGINCOMEPAE3) c/	LGMAXCREDIT	0.070	0.086	0.010	0.004	0.010	-0.047	0.037	0.050
		(3.24)***	(1.94)*	(0.69)	(0.12)	(0.55)	(1.10)	(3.89)***	(2.87)***
	RESID		-0.019		0.007		0.047		-0.016
			(0.39)		(0.25)		(1.34)		(0.84)

Robust t statistics in parentheses

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

a/ Income per adult equivalent 1 follows the approach developed by Rothbarth (1943), and it has been used by the Mexican government to identify poverty lines at national and local level.

b/ Income per adult equivalent 2 follows the approach developed by Wagstaff and van Doorslaer (1998).

c/ Income per adult equivalent 3 follows the OECD modified equivalence scale based on the work of Hagenarrs et. al, (1998).

Notice that the predicted residuals from the second-stage Tobit selection equation report statistically insignificant levels in the parameter estimates υ, confirming, as in the Heckit procedure, the assumption of no selectivity[13]. It is possible to argue thus that the decision process that involves increasing levels of borrowing is largely a function of the policy-specifics that are exogenously determined, and linearly correlated to progressive lending (captured by the length of membership).

The parameter estimate δ of the impact variable, C_i, reported a positive sign for each of the three microfinance organisations; however, the coefficients were only significantly different from zero in the case of Fincomun. More precisely, the econometric results suggest that if the maximum amount of capital borrowed by treatment households had gone up by x%, the income per adult equivalent 1 had increased in the order of 0.064x% relative to the control group, *ceteris paribus*. This result is important for two reasons:

First, it confirms that our findings are in line with the statistically significant impacts that we reported in equation 12; however, by substituting C_i for I_i we were able to discount the effects that older borrowers have on the average impact of programme participation, allowing us to obtain a more accurate estimation. Second, our results confirm the findings of other researchers (e.g. Morduch 1998; Coleman 1999) in relation to the small (or insignificant) effects that microcredit has on the level of individual income.

However, we could expect that an *absolute change* in the level of income, deriving from a *proportional change* in earnings relative to a change in the maximum amount of capital borrowed is heavily dependent on the level of

[13] The Hausman test also imposed the assumption of exogeneity, by no rejecting the null of no systematic difference between the covariance matrixes of the OLS and the 2S-Tobit estimators: $\chi^2(13) = 0.24$ in the case of Fincomun; $\chi^2(13) = 0.13$ in the case of CAME, and $\chi^2(12) = 2.11$ in the case of Promujer.

initial welfare. In other words, if we are interested in examining poverty impacts, we should expect larger effects from credit amongst those households who are better off. We examine this particular issue in section 4 by looking at the relationship between the severity of deprivation and poverty impacts from the case-study organisations.

4. The impact of credit on poverty reduction

To begin the discussion, we proceed to calculate the incidence of poverty and poverty gap amongst households' members by computing four different monetary thresholds of income deprivation:

Poverty line 1 (PL1). It measures the incidence of *extreme poverty*, and has been calculated at 784.5 pesos per month.

Poverty line 2 (PL2). It measures the incidence of *poverty*, and has been computed at 1507.5 pesos per month.

Poverty line 3 (PL3). It measures the incidence of *moderate poverty* and has been calculated at 1881 pesos per month

World Bank's poverty line, which is fixed at US$ 2 a day

The use of several critical thresholds of human deprivation is justified for two reasons: firstly, there is a widespread recognition that the conventional relative poverty line of US $2 a day is too low for the existing domestic prices in the country. Secondly, by computing several poverty lines we were able to analyse how deep the case-study organisations were reaching the poor, and to measure the magnitude of the poverty impacts by levels of deprivation.

We followed the Sedesol (2002) criteria to identify the PL1 as the lowest threshold of income required to fulfil the minimum nutritional requirements to have a healthy living. A *food-based poverty line*. The PL2 includes the basket of basic goods plus other components such as health care and basic education. A *capabilities-based poverty line*. The PL3 adds to the PL2 components that are considered as important in a social context, such as housing, clothing and public transport. An *asset-based poverty line*. These poverty lines have been derived for the urban context.

The estimation of the incidence of poverty and poverty gap are presented in table 9. Incidence of poverty has been computed as the percentage of programme participants whose income per adult equivalent 1 was below the selected poverty line. In other words, the incidence of poverty (also known as headcount index) shows the share of households that could not afford to buy the basket of basic goods that was previously selected by the INEGI-ECLAC (1993). We have also estimated the poverty gap by estimating the mean aggregate income per adult equivalent shortfall relative to the poverty line across the sample.

Table 9 Poverty and human deprivation amongst programme participants
Figures in percentages

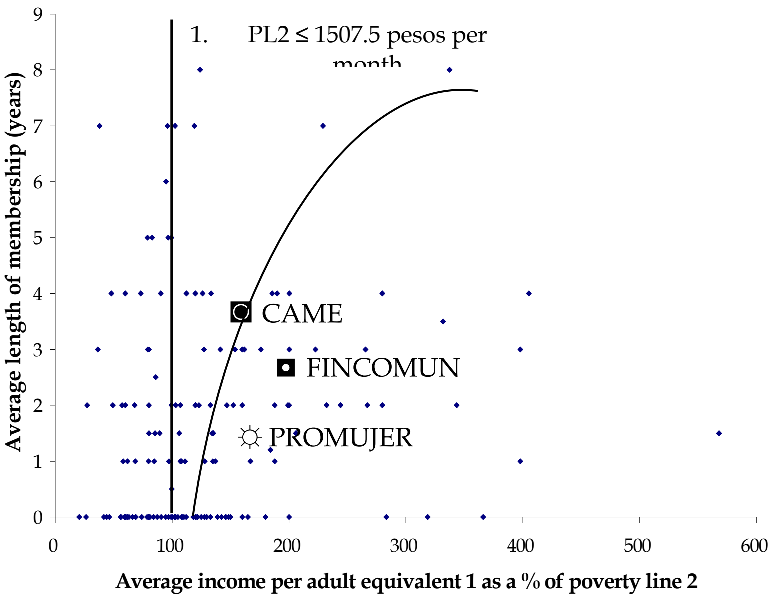
Concept	Sample size	FINCOMUN		CAME		PROMUJER	
		Control	Treated	Control	Treated	Control	Treated
Overall	148	34.5	65.5	39.1	60.9	44.7	55.3
Incidence of extreme poverty (PL1) c/							
≤ 784.5 pesos per month	10	15.8	11.1	11.2	0	0	3.9
Poverty gap		43.4	28.2	13.5	0	0	5.1
Depth of poverty (in pesos)		341	221	106	0	0	43
Incidence of poverty (PL2)							
≤ 1507.5 pesos per month	60	63.2***	27.8	50.0	42.9	33.3	38.5
Poverty gap		38.1	36.2	35.0	20.2	17.5	21.2
Depth of poverty (in pesos)		574	545	527	304	263	319
Incidence of moderate poverty (PL3)							
≤ 1881 pesos per month	87	73.7**	36.1	77.8	67.9	61.9	53.9
Poverty gap		44.8	39.3	34.1	25.4	23.3	30.6
Depth of poverty (in pesos)		842	738	642	477	439	576
World Bank's poverty line							
≤ US$ 2 a day	7	15.8	8.3	5.6	0	0	0
Poverty gap		33.6	23.7	1.1	0	0	0
Depth of poverty (in pesos)		225	159	7	0	0	0

The statistically significant association in the cross-tabulations are indicated by the Chi-square values for the cell as a whole at 0.001 (*); 0.01 (**); 0.05 (***); and 0.1 (****) levels of significance.
c/ Poverty lines are derived in prices of 2004, following Sedesol (2002)

We observed a larger incidence of poverty amongst treatment households at CAME and Promujer than at Fincomun when PL2 and PL3 were employed. For example, although 43% and 39% of treatment households at CAME and

Promujer, respectively, reported earnings that were below the minimum requirement to satisfy their basic needs according to the PL2, in comparison to 28% at Fincomun, only in the case of Fincomun we found a statistically significant association at 0.05 level between treatment and control groups in relation to the incidence of poverty. More precisely, the empirical evidence may suggest a significant relationship between programme participation and poverty reduction. Unfortunately we did not collect panel data to confirm this relationship. What we can say, however, is that the case-study organisations were reaching the poor at different levels of deprivation. To illustrate this, take the case of the depth of deprivation amongst poor borrowers (see also figure 2).

Figure 2 The relationship between average borrower income and the length of membership



The computed poverty gap was larger amongst participants at Fincomun than at CAME and Promujer. Poor borrowers at Fincomun had to cover, *on average*, an income shortfall of 545 pesos per month in order to cross the PL2, whereas poor borrowers at CAME and Promujer had to cover only 304 and 319 pesos, respectively. As suggested before, we might have the case here where some organisations (e.g. Fincomun) are more effective at reducing the number of poor households but only by lifting those who were closest to the poverty line, with low impacts on the poverty gap. Other organisations (e.g. CAME and

Promujer) might be more effective in reaching the extreme poor but by doing so, they report low insignificant effects on the overall incidence, bringing the extreme poor closer to the poverty line. One way to find out whether our assumptions are correct is by estimating the marginal effects of borrowing across the poverty lines. In order to do so, we ran a Probit estimation equation in the form

$$PL_i = \alpha_i + \delta C_i + u_i \tag{21}$$

where the dependent variable PL_i is a binary variable that takes the values

$$\mathrm{PL_i} = \begin{cases} 1 \text{ if } i^{th} \text{ household is below the poverty line} \\ 0 \quad \text{otherwise} \end{cases}$$

and C_i is the same continuous variable in equation (22) that measures the maximum amount of credit borrowed in logarithmic form. We have run (25) with PL_i adopting different poverty lines and using by default the definition of income per adult equivalent 1. In this sense PL_i was coded as POORPL1 when households were below the incidence of extreme poverty, PL1; POORPL2, when households were below the PL2; POORPL3, when households were below PL3, and POOR2US when households were below the World Bank's 2 US dollar a day poverty line. For comparative purposes, we have also run 25 with I_i as a substitute for C_i where I_i is the dichotomous variable previously defined with value $I = 1$ for treatment households and $I = 0$ for control groups.

By estimating the marginal effects of C_i we were able to capture in δ the impact of *a relative change in the amount of capital borrowed by a poor household* on the probability of staying below the poverty line. Alternatively, if we included I_i in the Probit equation, we were able to capture in δ the impact of *the individual choice of a poor household to participate in a credit programme* on the probability of staying in poverty. We present the results in table 10. Our findings reveal interesting information regarding the level penetration of the case-study organisations and their poverty impacts:

Table 10 Probit: the effect of programme participation on the probability of staying in poverty
Explanatory variable: Dummy variable for treatment group = 1

Independent variable: Dummy variable = 1 if IAE1 ≤ poverty line a/		FINCOMUN		CAME		PROMUJER		Pooled sample	
		(25) with I_i	(25) with C_i	.25) with I_i	(25) with C_i	(25) with I_i	(25) with C_i	(25) With I_i	(25) with C_i
World Bank poverty line ≤ US $2 a day	Coef	-0.379	-0.051					-0.350	-0.419
		(0.82)	(1.12)					(0.98)	(1.08)
	$\frac{\partial\Phi}{\partial \mathbf{X}}$	-0.074	-0.009					-0.036	-0.003
		(0.82)	(1.12)					(0.98)	(1.08)
Incidence of extreme poverty PL1 ≤ 784.5 pesos per month	Coef	-0.217	-0.029				0.178	-0.229	-0.027
		(0.49)	(0.66)				(5.83)***	(0.72)	(0.79)
	$\frac{\partial\Phi}{\partial \mathbf{X}}$	-0.046	-0.006				0.003	-0.031	-0.003
		(0.49)	(0.66)				(5.83)***	(0.72)	(0.79)
Incidence of poverty PL2 ≤ 1507.5 pesos per month	Coef	-0.925	-0.100	-0.180	-0.019	-0.137	-0.013	-0.327	-0.390
		(2.49)**	(2.58)***	(0.47)	(0.47)	(0.36)	(0.29)	(1.53)	(1.67)*
	$\frac{\partial\Phi}{\partial \mathbf{X}}$	-0.353	-0.038	- 0.071	-0.007	-0.051	-0.005	-0.127	-0.015
		(2.49)**	(2.58)***	(0.47)	(0.47)	(0.36)	(0.29)	(1.53)	(1.67)*
Incidence of moderate poverty PL3 ≤ 1881 pesos per month	Coef	-0.989	-0.108	-0.301	-0.030	-0.206	-0.029	-0.467	-0.055
		(2.61)***	(2.73)***	(0.72)	(0.70)	(0.55)	(0.64)	(2.15)**	(2.31)**
	$\frac{\partial\Phi}{\partial \mathbf{X}}$	-0.375	-0.043	-0.099	-0.010	-0.080	-0.011	-0.178	-0.021
		(2.61)***	(2.73)***	(0.72)	(0.70)	(0.55)	(0.64)	(2.15)**	(2.31)**

Robust z statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%
a/ Income per adult equivalent 1 (IAE1) follows Rothbarth (1943)
Note: Equation (25) could not be estimated neither using the World Bank's poverty line nor the Poverty line 1, due to the fact that we did not observe treatment households at CAME, and control groups at Promujer whose income was below the thresholds of extreme deprivation. The immediate consequence of that was to face a typical case of perfect predict probability.

As we were expecting, the slope coefficient of C_i reported negative signs when POORPL2 and POORPL3 were included as dependent variables, but they only showed statistically significant levels when we estimated the Probit equation for programme participants at Fincomun. Other things held constant, the effect of a *relative* change of x% in the level of borrowing by poor members at Fincomun was a decline in the probability of staying below that poverty line of about –0.038x%, and the magnitude of this impact was marginally greater (-0.043x%) when POORPL2 was replaced for POORPL3 in the estimation.

Although the parameter δ reported negative signs when the extreme poor was included in the estimation (e.g. POORPL1 and POOR2US), it was not significantly different from zero. In other words, we could not find statistical evidence to confirm a poverty impact from Fincomun at the lowest point of deprivation, where the *extreme poor* were grouped. This might confirm our hypothesis with regard to the idea that some lenders are more effective at having poverty impacts but just at the upper limits of deprivation, where they can take those who are closest to the poverty line out of poverty.

Interestingly, Promujer reported *positive* signs and statistically significant levels in the slope coefficient of C_i when POORPL1 was computed as dependent variable. This suggests that, other things held constant, a relative change in the loan size of an extreme poor woman borrowing from Promujer will *increase* the probability of staying poor. The fact that the slope coefficient of C_i reported negative but insignificant levels when POORPL2 and POORPL3 were included in the estimation, suggests that Promujer might be effective in reaching the extreme poor but by doing so, the organisation is reporting impacts just on the poverty gap and not on the overall incidence, which may also explain the considerably smaller poverty gap reported by the organisation compared to that of Fincomun (see table 9). Surprisingly, although the slope coefficient of C_i showed negative signs, we could not find any statistical significance to confirm poverty impacts from CAME at the estimated thresholds of deprivation.

5. Concluding remarks

Our findings revealed that microfinance organisations reach the poor at different levels of deprivation; however, although reaching the poor has its own merits, it does not necessarily lead to poverty reduction: only one organisation (Fincomun) reported statistically significant, although very small poverty impacts at the upper limits of the poverty line where the moderate poor is located, suggesting a strong relationship between the level initial welfare and the magnitude of the poverty impact. Furthermore, those organisations that rely the financial operation on group lending technology (CAME and Promujer) appeared to be more effective in reducing the poverty gap but by doing so, they report insignificant impacts on the overall incidence.

The empirical evidence also points to a linkage between the insignificance of the poverty impacts and lending technology. The link can be tracked to some devices that microfinance organisations have traditionally employed to deal with the screening, monitoring and enforcement problems. In particular, we refer to the costs that periodical repayment schedules, which demand weekly compulsory meetings, generate to programme participants. As discussed earlier in section 2.2, we found an *elastic* responsiveness in the demand for credit as a result of a percentage increase in the opportunity cost of borrowing. In fact, borrowers at CAME reported the largest elasticity between the three organisations. This reflects the direct effect that weekly compulsory meetings have on income, in particular when households economically more dynamic, and closer to the poverty line, are forced to forego earnings for being required to attend sessions that often last for several hours.

To illustrate this, we estimated the opportunity cost of borrowing per credit cycle. After computing this cost on monthly basis, the data reveals that it represented about 21% of the poverty gap that poor households borrowing from CAME had to cover to cross the poverty line 2, relative to the 10% of the poverty gap that borrowers at Fincomun had to cover. These results have important policy implications. Rigid screening and monitoring devices such as periodical repayment schedules can increase the utility cost of borrowing to such a level that the efforts of poverty reduction can be undermined. In this sense, institutional efforts aimed to reduce these costs can have significant effects. However, more research is needed to examine in more detail the linkage between lending technology and poverty impacts.

Table 11: Summary of findings

	FINCOMUN	CAME	PROMUJER	Pooled sample
Sample size	55	46	47	148
Percentage of female borrowers	49	74	100	73
Lending technology	Individual lending	Village banking	Solidarity groups in co-operative groups	
Periodicity of loan collection	Weekly and fortnightly	Weekly	Weekly and fortnightly	
Compulsory meetings	NO	YES	YES	
Upper limits to progressive lending	NO	YES	YES	
Income-generating activities (as % of income sources)	79.49	73.12	65.22	73.18
Years in business (average)	5.78	4.24	5.34	5.16
Opportunity cost of borrowing per credit cycle (in pesos of 2004)	886	1008	540	824
Elasticity of demand for credit per additional unit of opportunity cost	1.61	1.72	1.51	1.66
Average income per adult equivalent per month (in pesos of 2004)	2286	1860	1901	2031
Proportion of borrowers below poverty line (%)	40	45.65	36.17	40.51
Average income of poor borrowers (in pesos of 2004)	946	1108	1211	1024
Income of poor borrowers as % of the poverty line	62.76	73.46	80.33	67.88
Did the organisation report a significant income impact with I_i as explanatory variable?				
Heckit	YES	NO	YES	YES
OLS	YES	NO	NO	YES
and with C_i as explanatory variable?				
2S-Tobit	NO	NO	NO	YES
OLS	YES	NO	NO	YES
Did the organisation report significant marginal effects of a change in the amount of capital borrowed on the probability of staying in poverty?	YES	NO	NO	YES
Did the organisation report significant marginal effects of programme participation on the probability of staying in poverty?	YES	NO	NO	NO

Source: Sample survey

Table 12. List of variables

Independent variables	Definition	Obs	Mean	S.D.	Min	Max
Contained in X_i						
AVEDU	Years of education	148	7.047	3.777	0	17
HOWNER	If household owns residence = 1	148	0.682	0.467	0	1
HESTATE	If house is still in construction = 1	148	0.791	0.408	0	1
TIMEBUS	Years in business	148	5.162	5.746	0	30
WWORKER	Number of household members with a waged job	148	0.547	0.703	0	3
DEPENDRATIO	Dependency ratio (number of children, students and old members / household size)	148	0.498	0.222	0.125	1
AGE	Age of borrower	148	42.189	10.846	19	74
WOMAN	If borrower is woman = 1	148	0.730	0.446	0	1
MARITAL	If borrower is in a relationship = 1	148	0.757	0.430	0	1
Contained in L_i						
ROSCAS	If borrower participates in rotating savings and credit association = 1	148	0.453	0.499	0	1
FORMALCREDIT	If borrower have received loans from institutional lenders = 1	148	0.054	0.227	0	1
MONEYLENDER	If borrower have received loans from moneylenders	148	0.095	0.294	0	1
Instrumental variables						
DISTANCE	Distance from branch to place of residence or business (in minutes)	148	32.365	21.716	10	100
MEMBERSHIP	Years of membership	148	1.704	1.944	0	8
LGOPPORTCOSTPC	Logarithm of the opportunity cost of borrowing per credit cycle	148	3.880	3.204	0	8.006
LGCOSTBORROWPC	Logarithm of the cost of borrowing per credit cycle	148	3.973	3.267	0	8.006
Dependent variables						
LGMAXCREDIT	Logarithm of the maximum amount of credit borrowed in the last credit cycle	148	5.475	4.466	0	10.621
LGINCOMEPC	Logarithm of income per capita	148	7.296	0.594	5.438	8.868
LGINCOMEPAE1	Logarithm of income per adult equivalent 1	148	7.452	0.571	5.733	9.055
LGINCOMEPAE2	Logarithm of income per adult equivalent 2	148	7.724	0.545	6.114	9.315
LGINCOMEPAE3	Logarithm of income per adult equivalent 3	148	7.895	0.543	6.324	9.512
POORPL1	If household's income is below poverty line 1 = 1	148	0.068	0.252	0	1
POORPL2	If household's income is below poverty line 2 = 1	148	0.405	0.493	0	1
POORPL3	If household's income is below poverty line 3 = 1	148	0.581	0.495	0	1
POOR2US	If household's income is below US $2 a day = 1	148	0.047	0.213	0	1

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