Final Version
March 30, 2007

MDGs and Microcredit: An Empirical Evaluation for Latin American Countries (*)

Ricardo Bebczuk and Francisco Haimovich

CEDLAS and Universidad Nacional de la Plata, Argentina

Abstract

This study uses for the first time household survey data from a number of Latin American countries to investigate the degree and effects of the access to credit on the income and education of poor households. With this goal in mind, multivariate regressions are run to estimate the impact of the credit to the poor on their labor income and on the probability of their children to stay at both primary and secondary school. Afterwards, based on these results, alternative credit policies are simulated. Much in line with the available microcredit evidence, the study provides mixed results: while no negative effects are identified, positive and significant loadings are found in several, but not all cases. The simulation exercises support the claim that microcredit might be a relatively powerful but still limited tool for meeting the MDGs.

(*) We acknowledge the financial support from UNDP. We also thank Enrique Ganuza for insightful comments. The usual disclaimer applies. Comments welcome at ricardob@lpsat.com.

Introduction

The microfinance field has been catching much attention from various circles over the last few years. This increasing awareness comes from the perception of microfinance as a tool to improve social conditions in developing countries. In the context of the ongoing international initiatives, microfinance appears a priori as a suitable instrument towards reaching the Millenium Development Goals (henceforth, MDG), in particular, (1) *Eradicate extreme poverty and hunger,* (2) *Achieve universal primary education, and* (3) *Promote gender equality and empower women*.

But although a considerable amount of work is being devoted to shed light on the key macroeconomic and institutional factors to promote this market, the micro-level analysis is so far an incipient item in the research agenda. Based on information from national household surveys of Latin American countries, our study aims at characterizing individuals and firms receiving credit, quantifying the effects of such loans on education and income, and simulating different microcredit policies as a policy instrument to reach the Millenium Development Goals. To the best of our knowledge, this is the first project using hard data from household surveys to analyze credit access in the region.

The paper is organized as follows: In Section 1 we review the theoretical and empirical literature. In Section 2 we describe the database. The econometric work is presented in Section 3, while the microsimulations are carried out in Section 4. Some discussion and conclusions close.

1. Literature Review and Working Hypotheses

Unlike plain subsidies, loans are supposed to be repaid. Consequently, they might have only a temporary effect on household consumption, unless the money is channeled toward investment in physical or human capital. Loans will boost income when invested in profitable investment projects, but not when devoted to current consumption.[1] Since we are concerned about microfinance as a potential tool to reduce poverty on a sustainable basis, we focus here on the role of credit in facilitating productive investment opportunities and improving children educational attainment.

A number of arguments can be advanced to support a positive relationship between child education and microfinance. It is well-known that the demand for education depends upon household preferences and background as well as income considerations (see Maldonado (2005)). By relaxing the budget constraint, loans can influence education decisions. As the marginal utility of income is quite high for poor households, primary and secondary education entails a steep opportunity cost, as children would not be able to work and contribute to household income. In the presence of adverse income shocks hitting poor households, children may drop out from school to get a job or to migrate with their families to other locations. Also, the access to microfinance services (not only microcredit) may have a positive information effect by reducing myopic behavior and raising awareness about future returns and opportunities associated to more education. The evidence to date is mixed: while Barnes (2001) claims a positive effect in Zimbabwe, Pitt and Khandker (1998) reach, for Bangladesh, a positive impact only when credit is granted to women, and Maldonado (2005) presents ambiguous results on Bolivia, where the availability of credit in rural activities has seemingly driven parents to use their children´s labor supply in new productive projects.

An intensely researched field since the early 1990s is the interplay between financial deepening and growth, which more recently has also embraced the role of finance as a poverty alleviation instrument. Credit can help improve income growth prospects by boosting either the volume or the productivity of investment. For financially constrained households, credit turns out to be key to exploit good productive projects that would

[1] In the latter case, there could be a positive welfare effect linked to consumption smoothing, but this goes beyond the scope of our work.

otherwise be passed up. On top of this, and even for household not facing financial constraints, borrowing can push up productivity of existing and new projects as:

(a) Formal and informal lenders screen applicants and select only those with adequate repayment ability. This selection process provides low cost information to entrepreneurs concerning the actual profitability of the business plans and should lead them to discard those with a bleak outlook;

(b) The effort devoted to the project may be reinforced in the face of a fixed financial obligation and the psychological and pecuniary costs of not fulfilling it, such as reputation losses and shutting down of the business;

(c) Banks are especially well equipped to establish close lending relationships with their clients to struggle with their informational handicap and assess the actual character and expected cash flows of the borrower. Microfinance institutions take fuller advantage of these relationships than formal institutions. Given their proximity to the borrowers and a smaller and more manageable loan portfolio, these institutions pay frequent visits to the business and household, talking with the entrepreneur and their relatives and partners to draw valuable information and prevent in advance inefficient and opportunistic decisions on the part of the borrower;

(d) Adding to this, the microlending technology encompasses a variety of incentive devices to ensure debt repayment, such as group lending (all borrowers within each group are held responsible if any member defaults), progressive schemes (performing borrowers are granted increasing amounts and terms in subsequent rounds of borrowing), and short-term, revolving lending to facilitate monitoring; and

(e) Most microcredit programs include technical assistance and other supporting learning activities that may provide beneficial guidance to entrepreneurs.

At the macroeconomic level, Beck, Demirguc-Kunt and Levine (2004) find a strongly positive impact of financial development on poverty and income inequality reduction for a broad sample of 52 countries over the 1960-1999 period, after running a number of multivariate cross-section regressions. Other contributions to the subject, such as Li, Squire and Zou (1998), Clarke, Xu and Zou (2003) and Honohan (2004), reach similar conclusions. One debatable aspect of these studies has to do with the fact that formal credit markets do not appear to massively serve the poor, casting some doubt on the actual channels through which formal financial deepening works to reduce poverty and whether this positive effect is not picking up the impact of other omitted variables.

Poor individuals and small firms find it particularly difficult to enter credit markets because of asymmetric information frictions, namely, the fact that borrowers are more informed than creditors with respect to the actual ability and willingness to repay (see Bebczuk (2003a)). As small firms and consumers have less reliable accounting information (if any) and display no credit track record, they appear as more opaque in the eyes of the potential providers of funds, who prefer to do business with reputable and transparent large enterprises. As a result, creditors end up rationing credit, requiring higher returns and shortening maturities on the former groups, giving rise to financial constraints, which have been documented for both large and small companies throughout the world (see Galindo and Schiantarelli (2002) and Bebczuk et al. (2003b)). These informational barriers, compounded by the high fixed costs of screening and monitoring small scale loans and the lack of collateral to back such operations, seem to break the alleged finance-poverty nexus, as the poor mostly rely on informal credit markets, NGOs, and relatives. Consequently, a more dependable approach to determine the nexus between credit and poverty is to run micro studies on individuals and families with and without access to credit. Khandker (1998, 2003) and Barnes (2001) follow this procedure for particular microcredit programs in Bangladesh and Zimbabwe, respectively. Meyer (2002), in surveying the available evidence for Asian countries, contends that, while there seems to be an overall positive effect on income and education, results substantially differ across countries and programs in magnitude as well as statistical significance and robustness.

In spite of its expected benefits for income and education outcomes, it would be naïve to assert that credit will always deliver on its promises. For instance, there could be a moral hazard behavior at play, inducing entrepreneurs to divert loans to current consumption instead of investment projects, or merely to substitute self-financing for debt. In this sense, Simtowe, Zeller and Phiri (2006) find some evidence of moral hazard in joint liability lending schemes in credit groups in Malawi. People with low education or business skills are equally prone not to make a profitable use of loans. Likewise, loans may not automatically change household education preferences, even after enhancing income levels and security. The amount of credit the household gets may also influence the observed impact. Small loans (as a fraction of current household income) are less likely to help reshape educational choices of poor families, provided the additional money does not take them out of the subsistence level or do not create any sense of income security. For entrepreneurs, credits should be high enough to allow them undertake their projects. When projects are indivisible and the entrepreneur is unable to reach the minimum required funding, business plans are bound to be abandoned.[2] In a similar vein, the borrower is likely to make different choices according to the maturity and expected rollover of the loan - for instance, he or she will be less inclined to make productive investments when receiving a non-renewable, short-term loan.

Gender issues have a central role in the microcredit debate. Several programs are targeted to women under the premise that women are most frequently excluded from formal credit and labor markets, and because they do not equitably share power with men within household units. More importantly, women are often thought to have a heavier preference, vis-à-vis men, for their children welfare, giving rise to a more efficient intra-household allocation of resources. For instance, scholars contend that women have a stronger preference for children education (see Behrman and Rozenweig (2002)). The evidence from Pitt and Khandker (1998), Panjaitan-Drioadisuryo and Cloud (1999) and Pitt, Khandker and Cartwright (2003) reveals that loans to women have a greater positive effect on measures of consumption, health and nutrition than loans extended to men.

[2] Clearly, the term of the loan and the likelihood to roll it over may be equally important. Unfortunately, as mentioned earlier, no household survey provides such sort of information.

2. Descriptive statistics

Before going into the estimations, we will describe the content and main features of the database, which our study will exploit for the first time. The Socioeconomic Dataset for Latin America and Caribbean (SEDLAC) was assembled by the Centro de Estudios Distributivos, Laborales y Sociales (CEDLAS), Universidad Nacional de La Plata, Argentina. Details on methodology and coverage can be found in Gasparini, Gutiérrez, Támola, Tornarolli and Porto (2005). This unique database puts together all the finance-related questions asked in Latin American Household Surveys since the 1990s. We will focus on the questions asking whether and how much credit each household and each enterprise received during the last year. Table 1 lists the countries and years for which credit information is available: Bolivia (2002), Guatemala (2000), Jamaica (1999), Mexico (2002), Nicaragua (1993, 1998 and 2001), Peru (1997, 1999, and 2002), Paraguay (2001), and Haiti (2001). Except for Nicaragua (2001) and Haiti (2001), which only collect information on credit to enterprises, the remaining surveys report loans made directly to the household. The same table also gives a micro flavor of the much discussed shallowness of the financial system in Latin America: on average, only 6.8% of the households receive any credit, with a minimum of 1.3% in Perú (2002) and a maximum of 16.9% in Nicaragua (1998). Since in Mexico and Peru the survey asks about specific lines of credit for housing and education (see Table 1), the fraction of total households with such specific loans is below 5%.[3] However, similar ratios are found in other surveys, like Paraguay (2001) and Nicaragua (1993). When looking at poor households only, it appears that the proportion getting credit is higher on average than for the whole population (9.2% against 6.8%) and, even in the cases where the proportion is lower than the average, the gap is small.

[3] This also justifies that the number of households responding on credit access is noticeably lower than the total number of households in several surveys, as they ask only to the group of potential borrowers.

Table 1
Access to Credit by Households in Latin America

Country	Year	Number of Households	Number of Households asked about credit	Individuals asked about credit	Type of credit asked about	% of total households receiving credit	% of poor households receiving credit
Bolivia	2002	5746	5746	Adults	Not specific	12,4	7,2
Guatemala	2000	7276	7260	Head	Not specific	11,1	9,1
Haiti	2001	7186	5879	Head	For enterprises	9,0	11,9
Mexico	2002	17167	17167	All	For home purchase or improvement, and tertiary education	1,5	1,3
Nicaragua	1993	4454	4449	Head	Not specific	3,5	2,2
Nicaragua	1998	4040	4009	Head	Not specific	16,9	11,8
Nicaragua	2001	4191	1565	Adults	For enterprises	6,7	12,6
Perú	1997	6487	750	Head	For home improvement	3,0	14,5
Perú	1999	3517	547	Head	For home improvement	5,0	24,4
Perú	2002	18598	2001	Head	For home improvement	1,3	3,0
Paraguay	2001	8131	8127	Head	Not specific	4,3	3,3
Average						*6,8*	*9,2*

Source: Own elaboration based on SEDLAC.

Next we present information for working individuals classified into entrepreneurs, salaried and self-employed. We observe that the proportion of workers with access to credit is still low and similar across groups –ranging from 11.7% for the self-employed to 13.7% for entrepreneurs- but, unlike the household-level data, poor workers appear to be slightly below overall figures (between 8.1% for the self-employed and 10.2% for the salaried).

Table 2
Percentage of individuals with credit, by labor status

Country	Year	Entrepreneurs		Salaried		Self-employed	
		All	Poor	All	Poor	All	Poor
Bolivia	2002	9,4	8,0	6,6	3,5	7,2	4,4
Guatemala	2000	13,5	10,2	11,9	8,8	9,7	9,2
Haiti	2001	0,0	0,0	9,2	11,4	13,7	14,3
Mexico	2002	0,7	1,2	1,1	0,2	0,5	0,6
Nicaragua	1993	3,2	10,8	1,9	1,4	6,5	3,9
Nicaragua	1998	27,4	19,7	16,3	11,2	20,5	12,7
Nicaragua	2001	19,6	15,2	7,6	9,2	15,3	11,7
Perú	1997	23,9	0,0	28,2	13,7	18,7	5,7
Perú	1999	35,2	22,7	42,6	46,7	24,6	20,7
Perú	2002	12,8	0,0	19,8	4,3	7,4	2,4
Paraguay	2001	4,8	14,0	4,7	2,1	4,2	3,8
Average		*13,7*	*9,3*	*13,6*	*10,2*	*11,7*	*8,1*

Source: Own elaboration based on SEDLAC.

Regarding quantities, and based on the information available for Guatemala, Nicaragua and Peru presented in Table 3, we conclude that the amount of credit, in current dollars, is about US$1,100 on average for the whole sample and US$500 for poor households. However, as a proportion of household income, it is not clear that poor households receive less credit than others. In fact, the ratio between average credit and average household income, as well as the median credit to income ratio for borrowing households (columns 4 and 8 in Table 3).

Table 3

Amount of Credit to Households
In current U.S. dollars, unless stated otherwise

Country	Year	All Households				Poor Households			
		Average credit	Total Household Income	Credit to Household Income (%)	Credit to Household Median	Average credit	Total Household Income	Credit to Household Income (%)	Credit to Household Median
		(1)	(2)	(3)=[(1)/(2)]*100	(4)	(5)	(6)	(7)=[(5)/(6)]*100	(8)
Guatemala	2000	1310.2	4767.8	27.5	8.9	237.2	1216.8	19.5	10.8
Nicaragua	1993	1706.7	3394.3	50.3	9.0	752.9	1328.6	56.7	14.5
Nicaragua	1998	659.3	3418.3	19.3	5.8	231.3	1279.4	18.1	8.2
Nicaragua	2001	731.2	3836.5	19.1	5.9	180.6	1426.9	12.7	6.5
Perú	1997	1591.1	5764.7	27.6	22.8	1428.2	1436.5	99.4	76.1
Perú	1999	867.3	5037.8	17.2	17.3	236.4	1237.1	19.1	9.7
Perú	2002	1102.3	4802.5	23.0	15.4	410.8	1195.2	34.4	25.1
Average		1138.3	4431.7	26.3	12.2	496.8	1302.9	37.1	21.6

In Table 4 we portrait the personal profile of working individuals receiving and not receiving credit, observing that borrowers tend to have higher total and hourly income, better education, and to live in urban areas. On the other hand, they do not seem to be clearly distinct from other individuals concerning their age or gender. These relative features remain mostly the same after restricting the sample only to poor individuals, although income differentials, especially for hourly values, narrow down (see Table 5).

Table 4

Income and Access to Credit, All Individuals

Country	Year	Labor Income (US$)		Hourly Labor Income (US$)		Age		Years of Education	
		No	Yes	No	Yes	No	Yes	No	Yes
Bolivia	2002	1545	2530	0.78	1.17	23.9	39.4	6.1	9.0
Guatemala	2000	2638	3487	1.26	1.72	44.7	41.0	3.9	5.1
Haiti	2001	503	622	0.43	0.46	47.5	45.3	3.4	3.3
Mexico	2002	5240	5638	2.47	2.65	28.0	28.1	6.2	11.3
Nicaragua	1993	2062	3619	1.01	2.04	44.2	42.9	4.0	5.5
Nicaragua	1998	1887	2525	0.93	1.14	45.7	43.8	4.2	5.8
Nicaragua	2001	2518	2924	1.27	1.44	42.2	42.3	5.4	5.9
Peru	1997	3021	4428	1.44	2.10	43.8	44.6	8.0	9.2
Peru	1999	1938	2432	0.88	1.26	46.9	44.9	7.4	8.8
Peru	2002	2259	2949	1.22	1.41	44.9	46.3	8.1	10.4
Paraguay	2001	3027	3107	1.41	1.36	46.6	46.0	6.5	6.8
Simple Average		*2422*	*3115*	*1.19*	*1.52*	*41.7*	*42.2*	*5.7*	*7.4*

(*) No (Yes): The individual does not receive (receives) credit.
Source: Own elaboration based on SEDLAC.

Table 4 (cont.)

Income and Access to Credit, All Individuals (cont.)

Country	Year	Urban Dummy		Male Dummy		Female Head Dummy	
		No	Yes	No	Yes	No	Yes
Bolivia	2002	0.62	0.81	0.50	0.53	0.15	0.17
Guatemala	2000	0.43	0.47	0.81	0.86	0.19	0.14
Haiti	2001	0.29	0.32	0.50	0.44	0.50	0.56
Mexico	2002	0.75	0.82	0.64	0.65	0.18	0.15
Nicaragua	1993	0.58	0.62	0.71	0.79	0.29	0.21
Nicaragua	1998	0.54	0.71	0.72	0.72	0.28	0.28
Nicaragua	2001	0.76	0.80	0.47	0.31	0.31	0.33
Peru	1997	0.67	0.93	0.83	0.83	0.17	0.17
Peru	1999	0.63	0.80	0.81	0.87	0.19	0.13
Peru	2002	0.63	0.86	0.83	0.80	0.17	0.20
Paraguay	2001	0.56	0.69	0.75	0.75	0.25	0.25
Simple Average		*0.59*	*0.71*	*0.69*	*0.69*	*0.24*	*0.24*

(*) No (Yes): The individual does not receive (receives) credit.
Source: Own elaboration based on SEDLAC.

Table 5
Income and Access to Credit, Poor Individuals

Country	Year	Labor Income (US$)		Hourly Labor Income (US$)		Age		Years of Education	
		No	Yes	No	Yes	No	Yes	No	Yes
Bolivia	2002	486	641	0.27	0.30	22.3	40.1	4.3	5.4
Guatemala	2000	754	882	0.28	0.39	42.9	40.5	2.0	1.4
Haiti	2001	306	362	0.27	0.32	46.9	45.3	2.7	2.6
Mexico	2002	1289	1177	0.69	0.56	24.7	27.5	3.9	7.1
Nicaragua	1993	872	1120	0.49	0.52	44.3	45.3	2.5	3.4
Nicaragua	1998	737	839	0.38	0.43	45.4	43.3	2.8	4.2
Nicaragua	2001	729	937	0.53	0.59	40.2	41.3	3.6	4.3
Peru	1997	961	1244	0.71	0.77	42.5	44.7	4.5	7.3
Peru	1999	852	799	0.56	0.48	47.1	43.7	3.9	5.2
Peru	2002	751	754	0.41	0.41	42.0	44.5	5.7	5.9
Paraguay	2001	611	639	0.31	0.32	46.6	47.4	3.9	4.1
Simple Average		*759*	*854*	*0.45*	*0.46*	*40.4*	*42.1*	*3.6*	*4.6*

(*) No (Yes): The individual does not receive (receives) credit.
Source: Own elaboration based on SEDLAC.

Table 5 (cont.)
Income and Access to Credit, Poor Individuals (cont.)

Country	Year	Urban Dummy		Male Dummy		Female Head Dummy	
		No	Yes	No	Yes	No	Yes
Bolivia	2002	0.38	0.53	0.50	0.56	0.11	0.12
Guatemala	2000	0.25	0.13	0.84	0.89	0.16	0.11
Haiti	2001	0.24	0.26	0.49	0.46	0.51	0.54
Mexico	2002	0.46	0.52	0.63	0.48	0.17	0.34
Nicaragua	1993	0.43	0.39	0.74	0.74	0.26	0.26
Nicaragua	1998	0.44	0.60	0.73	0.71	0.27	0.29
Nicaragua	2001	0.66	0.84	0.45	0.26	0.37	0.37
Peru	1997	0.19	0.90	0.90	0.86	0.10	0.14
Peru	1999	0.23	0.43	0.83	0.88	0.17	0.12
Peru	2002	0.27	0.62	0.90	0.86	0.10	0.14
Paraguay	2001	0.23	0.15	0.78	0.82	0.22	0.18
Simple Average		0.34	0.49	0.71	0.68	0.22	0.24

(*) No (Yes): The individual does not receive (receives) credit.
Source: Own elaboration based on SEDLAC.

As for schooling, Tables 6 and 7 reveal that children from credit-receiving households display, on average, higher levels of primary and secondary school attendance. Furthermore, these households typically have higher per capita income, live in a city and have more educated parents.

Table 6

Primary School Attendance and Access to Credit

Country	Year	School Attendance Dummy		Per Capita Household Income (current US$)		Urban Dummy		Years of Education, Household Head		Years of Education, Household Adults	
		No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Bolivia	2002	0.93	0.97	482	795	0.56	0.77	6.48	8.50	5.53	7.53
Guatemala	2000	0.75	0.84	729	913	0.34	0.31	3.30	3.68	2.77	3.20
Haiti	2001	0.77	0.83	198	181	0.25	0.30	3.08	3.42	3.13	3.41
Mexico	2002	0.97	0.97	1379	1774	0.70	0.71	6.75	7.47	6.35	7.24
Nicaragua	1993	0.96	0.92	485	901	0.53	0.66	3.51	5.39	3.50	4.78
Nicaragua	1998	0.82	0.94	489	642	0.50	0.65	3.88	5.30	3.69	4.89
Nicaragua	2001	0.91	0.95	622	901	0.68	0.79	4.30	5.19	4.27	4.75
Peru	1997	0.95	0.98	827	1102	0.54	0.91	7.22	9.28	6.07	7.89
Peru	1999	0.97	0.96	586	749	0.52	0.71	7.19	7.78	6.15	6.46
Peru	2002	0.97	1.00	727	1186	0.57	0.78	7.84	9.95	6.65	8.65
Paraguay	2001	0.94	0.98	764	1006	0.46	0.58	6.00	6.26	5.47	5.73
Simple Average		0.90	0.94	663	923	0.51	0.65	5.41	6.57	4.87	5.87

(*) No (Yes): The individual does not receive (receives) credit.
Source: Own elaboration based on SEDLAC.

Table 7

Secondary School Attendance and Access to Credit

Country	Year	School Attendance Dummy		Per Capita Household Income (current US$)		Urban Dummy		Years of Education, Household Head		Years of Education, Household Adults	
		No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Bolivia	2002	0.82	0.89	562	820	0.60	0.75	6.61	8.20	5.80	7.31
Guatemala	2000	0.51	0.57	823	804	0.38	0.33	3.11	3.16	2.79	2.72
Haiti	2001	0.77	0.80	213	201	0.33	0.35	3.35	3.23	3.52	3.47
Mexico	2002	0.71	0.89	1619	2145	0.72	0.77	6.22	7.62	6.06	7.63
Nicaragua	1993	0.70	0.64	522	933	0.55	0.55	3.29	5.23	3.39	5.02
Nicaragua	1998	0.58	0.71	539	1092	0.51	0.70	3.67	5.39	3.67	5.17
Nicaragua	2001	0.75	0.76	896	906	0.71	0.81	4.57	6.20	4.61	5.58
Peru	1997	0.78	0.85	1283	1086	0.65	0.89	7.53	7.79	6.27	6.71
Peru	1999	0.81	0.92	771	946	0.57	0.69	7.34	8.25	6.17	6.93
Peru	2002	0.81	0.92	720	1250	0.57	0.84	7.23	10.13	5.95	8.91
Paraguay	2001	0.72	0.80	922	1087	0.51	0.59	6.00	6.39	5.48	5.86
Simple Average		*0.72*	*0.80*	*806*	*1024*	*0.55*	*0.66*	*5.36*	*6.51*	*4.88*	*5.94*

(*) No (Yes): The individual does not receive (receives) credit.
Source: Own elaboration based on SEDLAC.

3. Econometric Analysis

In what follows we discuss our empirical findings on the effect of credit on labor income (section 3.1) and primary and secondary schooling decisions (section 3.2) of poor households. Summarizing our subsequent remarks, we find that credit (proxied by a dummy with value one if the worker got a loan over the last 12 months) boosts labor income in a statistically and economically significant fashion in three out of the seven household surveys under study. In two out of four surveys with loan quantity data available, we observe an equally significant impact. As for education, the access to credit improves primary (secondary) school attainment in five (three) out of eleven household surveys, with the effect running through the ability to get credit and independently of the amount obtained.

3.1 Income Regressions

Our first econometric exercise centers on the impact of credit on the income of poor households. The dependent variable is the natural logarithm of the hourly labor income of the household head. We restrict the analysis to poor workers, as this is our population of interest and because, from an econometric standpoint, endogeneity caveats are largely mitigated when other income recipients are dropped from the sample. Since we are interested in assessing whether the access to credit raises labor income by allocating borrowed money to profitable productive projects, we exclude observations with zero income and those for salaried individuals: in the first case, because it is evident that the individual, even having received credit, did not allocate it to any productive project;[4] in the second case, because employed workers earning a salary do not undertake, by definition, investment projects by themselves.[5] Guided by this criterion, we also discarded the Mexico and Peru surveys because they explicitly state that the loan is not to be used for investment purposes. We perform two sets of regressions, one including just a dummy variable indicating whether the individual had any credit, and the other including the amount received. Besides the credit variables just described, we will control for schooling, age, gender, and residence (urban or rural).

[4] Alternatively, he or she might have allocated it to a project with nil gross revenue, a situation quite unlikely.

[5] Ideally, we would like survey respondents to clearly state whether the loan was used for consumption or investment. Since we lack such information, we follow this alternative approach. Of course, it is still possible that a self-employed or entrepreneur uses the loan consumption.

Baseline results for the credit dummy are reported in Table 8. The variable of interest yields a positive sign consistent with the usual prior, but it is statistically significant only in Bolivia (at 10%), Guatemala (at 1%), and Haiti (at 5%). The estimated coefficients imply that the access to credit would increase the hourly labor income of poor individuals currently without credit by 4.8, 12.5 and 4.5 times, respectively. We added a number of controls to avoid misspecification issues. While in general results are in line with the typical Mincerian hypotheses, this is not always the case. Worker age shows a non-linear effect in several in five out of seven regressions; the urban location is positive and significant in four cases, but significantly negative in one of them. Two positive and two negative significant estimates are found for gender. Self-employment (intended to capture lower income linked to informal and precarious jobs) is negative in three and positive in one case. Even more striking are the estimates for the different levels of school attainment. Against the expected positive and increasing values for higher schooling levels, we do not find any clear pattern in the estimates. One possible reason is that, for the typical poor worker, basic education is what makes a difference in terms of income. With this in mind, we redid in Table 9 our regressions replacing the multiple education dummies for one with value 1 if the individual has at least seven years of education, and zero otherwise. The resulting coefficient is positive in all cases and significant in three of them. Also important is that this change in the control set does not alter much the credit dummy coefficient.

Table 8

Credit Dummy and Labor Income: OLS Baseline Regressions

Dependent Variable: Ln(Hourly Labor Income)	Bolivia 2002	Guatemala 2000	Haiti 2001	Nicaragua 1993	Nicaragua 1998	Nicaragua 2001	Paraguay 2001
=1 if received a loan	0.274*	1.247***	0.197**	0.325	0.041	0.07	0.155
	[0.164]	[0.287]	[0.081]	[0.230]	[0.123]	[0.180]	[0.151]
=1 if s(he) is self-employed	-0.291*	0.804**	-0.845	-0.596	-0.451***	0.095	-0.673***
	[0.149]	[0.334]	[0.555]	[0.548]	[0.104]	[0.197]	[0.089]
=1 if primary school complete	0.401**	0.044	0.22	0.311*	-0.011	0.161	0.184*
	[0.164]	[0.370]	[0.231]	[0.175]	[0.125]	[0.189]	[0.101]
=1 if secondary school incomplete	0.432***	-0.228	-0.155	0.307*	0.243	0.275	0.29
	[0.117]	[0.423]	[0.185]	[0.174]	[0.164]	[0.297]	[0.186]
=1 if secondary school complete	0.298*	-0.165	-0.930***	0.940**	0.385**	-0.249	-0.034
	[0.178]	[0.910]	[0.102]	[0.461]	[0.181]	[0.656]	[0.227]
=1 if superior school incomplete	-0.094	1.656***	-0.809	-2.671***	0.58	0	0.135
	[0.389]	[0.373]	[0.569]	[0.253]	[0.554]	[0.000]	[0.437]
=1 if superior school complete	0.558**	0.810**	2.837*	0.772	-0.158	1.06	0.054
	[0.280]	[0.322]	[1.490]	[0.482]	[0.113]	[0.908]	[0.108]
Age	0.065***	0.157**	0.029	0.063**	-0.028	0.083*	0.046**
	[0.021]	[0.065]	[0.018]	[0.028]	[0.024]	[0.049]	[0.021]
Age squared	-0.001***	-0.002**	-0.000**	-0.001**	0	-0.001*	-0.001**
	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]
=1 if male	0.227**	0.376	0.162***	-0.221	-0.314***	0.018	-0.260*
	[0.101]	[0.468]	[0.058]	[0.163]	[0.111]	[0.151]	[0.138]
=1 if urban	0.847***	0	-0.578***	0.332**	0.248***	0.222	1.285*
	[0.085]	[0.000]	[0.078]	[0.130]	[0.094]	[0.139]	[0.692]
Constant	-4.250***	-6.572***	-1.420**	-1.411*	0.29	-3.055***	-3.156***
	[0.464]	[1.467]	[0.680]	[0.759]	[0.524]	[1.085]	[0.829]
Observations	1369	226	2294	853	821	228	1033
R-squared	0.23	0.18	0.09	0.21	0.13	0.08	0.17
Sigma	1.15	1.27	1.24	1.1	1.05	0.84	0.94

Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%
The regressions include unreported regional dummies.

Table 9

Credit Dummy and Labor Income: OLS Additional Regressions

Dependent Variable: Ln(Hourly Labor Income)	Bolivia 2002	Guatemala 2000	Haiti 2001	Nicaragua 1993	Nicaragua 1998	Nicaragua 2001	Paraguay 2001
=1 if received a loan	0.273*	1.164***	0.225***	0.25	0.061	0.078	0.178
	[0.162]	[0.280]	[0.084]	[0.235]	[0.128]	[0.176]	[0.147]
=1 if s(he) is self-employed	-0.293**	0.618**	-0.81	-0.692	-0.447***	0.071	-0.648***
	[0.149]	[0.305]	[0.587]	[0.545]	[0.104]	[0.241]	[0.086]
=1 if s(he) has at least 7 years of education	0.370***	0.312	0.121	0.445*	0.326***	0.362	0.066
	[0.095]	[0.373]	[0.089]	[0.232]	[0.110]	[0.378]	[0.188]
Age	0.064***	0.179***	0.028	0.066**	-0.026	0.085*	0.043**
	[0.020]	[0.069]	[0.018]	[0.028]	[0.024]	[0.050]	[0.022]
Age squared	-0.001***	-0.002***	-0.000**	-0.001***	0	-0.001*	-0.001**
	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]
=1 if male	0.221**	0.375	0.152***	-0.216	-0.298***	0.025	-0.252*
	[0.101]	[0.469]	[0.059]	[0.171]	[0.111]	[0.147]	[0.140]
=1 if urban	0.836***	0	-0.634***	0.354***	0.253***	0.223	1.351*
	[0.085]	[0.000]	[0.079]	[0.129]	[0.090]	[0.140]	[0.705]
Constant	-4.218***	-6.915***	-1.451**	-1.308*	0.281	-3.013***	-3.065***
	[0.462]	[1.481]	[0.712]	[0.777]	[0.528]	[1.105]	[0.831]
Observations	1370	233	2250	853	821	228	1033
R-squared	0.23	0.15	0.08	0.2	0.13	0.07	0.17
Sigma	1.15	1.28	1.24	1.11	1.05	0.85	0.94

Notes:
Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%
The regressions include unreported regional dummies.

We go a step further in Tables 10 and 11 by entering the amount of credit instead of the loan dummy for the four cases available: Guatemala (2000) and Nicaragua (1993, 1998, and 2001). The coefficient is positive and significant (at a 10% level) only in Guatemala. Quantitatively, the estimated value suggest that an increase of 10% in the amount of credit from the average amount (US$237) translates into an increase in hourly labor income of 4.7 times with respect to the average income of current borrowers, and of 6.2 times for those without credit. In this sense, the results reproduce the high sensitivity of income to credit found in previous regressions.

Table 10

Credit Amount and Labor Income: OLS Baseline Regressions

Dependent Variable: Ln(Hourly Labor Income)	Guatemala 2000	Nicaragua 1993	Nicaragua 1998	Nicaragua 2001
Loan amount	0.002*	0	0	0.001
	[0.001]	[0.000]	[0.000]	[0.001]
=1 if s(he) is self-employed	0.876**	-0.624	-0.440***	0.092
	[0.360]	[0.523]	[0.105]	[0.194]
=1 if primary school complete	-0.091	0.304*	-0.024	0.152
	[0.368]	[0.175]	[0.125]	[0.191]
=1 if secondary school incomplete	-0.438	0.320*	0.244	0.276
	[0.432]	[0.174]	[0.169]	[0.297]
=1 if secondary school complete	-0.323	0.931**	0.393**	-0.427
	[0.901]	[0.458]	[0.181]	[0.522]
=1 if superior school incomplete	1.628***	0	0.589	0
	[0.390]	[0.000]	[0.554]	[0.000]
=1 if superior school complete	0.522	0.884	-0.147	1.059
	[0.373]	[0.571]	[0.112]	[0.905]
Age	0.158**	0.064**	-0.028	0.081*
	[0.068]	[0.028]	[0.024]	[0.049]
Age squared	-0.002**	-0.001**	0	-0.001*
	[0.001]	[0.000]	[0.000]	[0.001]
=1 if male	0.396	-0.224	-0.319***	0.026
	[0.484]	[0.163]	[0.111]	[0.151]
=1 if urban	0	0.337***	0.237**	0.221
	[0.000]	[0.130]	[0.093]	[0.139]
Constant	-6.360***	-1.404*	0.3	-3.014***
	[1.522]	[0.741]	[0.518]	[1.083]
Observations	226	851	823	228
R-squared	0.14	0.2	0.13	0.09
Sigma	1.3	1.1	1.05	0.84

Notes:
Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%
The regressions include unreported regional dummies.

Table 11
Credit Amount and Labor Income: OLS Additional Regressions

Dependent Variable: Ln(Hourly Labor Income)	Guatemala 2000	Nicaragua 1993	Nicaragua 1998	Nicaragua 2001
Loan amount	0.002*	0	0.001	0.001
	[0.001]	[0.000]	[0.000]	[0.000]
=1 if s(he) is self-employed	0.706**	-0.695	-0.436***	0.063
	[0.331]	[0.528]	[0.104]	[0.248]
=1 if s(he) has at least 7 years of education	0.136	0.527**	0.333***	0.254
	[0.395]	[0.226]	[0.110]	[0.266]
Age	0.187***	0.066**	-0.026	0.086*
	[0.071]	[0.028]	[0.024]	[0.050]
Age squared	-0.002***	-0.001***	0	-0.001*
	[0.001]	[0.000]	[0.000]	[0.001]
=1 if male	0.389	-0.208	-0.304***	0.038
	[0.483]	[0.171]	[0.111]	[0.150]
=1 if urban	0	0.376***	0.243***	0.221
	[0.000]	[0.128]	[0.090]	[0.137]
Constant	-6.960***	-1.331*	0.291	-3.017***
	[1.564]	[0.764]	[0.527]	[1.090]
Observations	233	851	823	228
R-squared	0.11	0.2	0.13	0.07
Sigma	1.3	1.11	1.05	0.85

Notes:
Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%
The regressions include unreported regional dummies.

As announced in the Introduction, we explored in unreported exercises the role of gender. In particular, we wanted to assess whether female household heads allocate loans more efficiently than male heads. To this end, in addition to the credit variables included in the previous regressiones, we included the interaction of those variables with a dummy taking the value one for households with a female head, and zero otherwise. However, in no case did we find a significant gender effect.

One controversial issue is whether the significance of the credit coefficient is picking up the regressor endogeneity, as it may be claimed that there might exist reverse causality from income to credit on the grounds that high income earners are more likely to have access to credit in view of their enhanced ability to repay. However, we strongly believe that this argument does not go through when the sample is restricted to poor households. Two reasons can be invoked: for one, income dispersion is rather small among working poor individuals, so, from the lender´s perspective, the ability to repay is unlikely to vary substantially between two given poor borrowers in spite of narrow income differences. Second, commercial banks are usually not prone to extend credit to members of these income groups, which mostly rely on public or publicly sponsored microcredit programs where credit allocation is not necessarily governed by the borrower´s financial strength –it may even be the case that some programs target extremely poor households as a poverty reduction mechanism.[6]

Another concern has to do with the potential presence of selection bias. Let us recall that we are primarily interested in testing how the access to credit affects labor income, and that is why we excluded from our estimations all unemployed household headsbecause, by definition, the gross return on their loans –in case they got one- is zero. Nevertheless, in order to make sure that our results are not driven by selection bias, we re-run our baseline regressions from Table 8 and 10 but adding to the sample the unemployed household heads and using the two-step Heckman technique. The estimated coefficients did not change much: relative to the credit dummy estimates of Table 8, the coefficients for Bolivia, Guatemala and Haiti fell by just 3.4%, 0.2% and 3.1%, respectively, while no variation was found in the credit amount regressions. The regression output is not reported, but it is available upon request.

3.2 Education Regressions

We employ probit regressions to estimate the probability of attending primary and secondary school for children of 6 to 12 and 13 to 17 years old, respectively. Our variable of interest is whether the household received a loan during the last 12 months (and alternatively how much it received as a ratio of total household income). In order to take into account other schooling determinants, we include several controls. Invoking the arguments of the last paragraph, we expect that the higher the per capita household income, the higher the attendance. Households from rural areas should also exhibit lower education levels, owing to likely higher distance to schools, more child labor and higher income risk. The preference for education may be encouraged by more educated

[6] An alternative procedure is to instrumentalize credit. In unreported regressions (available upon request), we take the reception of remittances as such an instrument under the hypothesis that remittances might be a substitute for credit and that they are to a great extent exogenous to the recipient, but results were rather poor. However, it must be noted that finding the right instruments is always a difficult task (see Angrist and Krueger (2001)). Moreover, as long as the instruments are weak, the resulting coefficient may turn out to be inconsistent, creating an additional problem of their own (see Bound, Jaeger and Baker (1995)).

household heads, as measured by his or her years of education. Child age and gender are also included, although the expected sign is ambiguous. Regarding age, it might be the case that older children are perceived to have a larger labor opportunity cost, but on the other hand it is possible that younger children stay at home beyond the age of 6.[7] As for gender, it is an empirical question whether boys or girls are more likely to prematurely enter the labor market. A priori, boys may start working before girls, but girls are sometimes required to take care of household chores, including babysitting for younger siblings. An important issue is the role of female household heads in education decisions. In line with our previous discussion, we expect the probability of staying at school to be higher in households receiving credit and with a female head.[8]

Next we report the marginal probabilities of staying in primary school obtained from the probit regressions. Since we do not suspect any endogeneity bias contaminating the results, we first run regressions for the whole sample. In Table 12A and 12B we present the cases where the credit dummy was and was not significantly positive, respectively. Having access to credit significantly improves the probability of staying at school in Bolivia (2002), Guatemala (2000), Haiti (2001), Mexico (2002), and Nicaragua (1998 and 2001). The rise in probability ranges from 2.3% in Bolivia to 9.2% in Nicaragua (1998). The additional controls that deliver positive and significant loadings in most (but, as earlier, not in all) cases are Age, Per capita household income, the Urban dummy, and Years of education of the household head. The presence of a female household head shows the expected positive sign at acceptable significance levels in four out of the eleven regressions.

[7] It must be borne in mind that the mandatory primary school status in most countries is not always properly enforced.

[8] Marchionni and Sosa Escudero (1999), however, find for Argentina that secondary schooling is negatively correlated with the presence of a female head, which might stem from the fact that these women are divorced or single parents and thus need their children to work. These authors also stress the difficulty to isolate the effect of the different explanatory variables. For example, well educated parents will also have higher incomes.

Table 12A

Credit Dummy and Primary Education: Marginal Probabilities
All Households

Dependent Variable: Probability of Staying in Primary School	Bolivia 2002	Guatemala 2000	Haiti 2001	Mexico 2002	Nicaragua 1998	Nicaragua 2001
=1 if Household Received a Loan	0.023***	0.063***	0.042***	0.017***	0.092***	0.031**
	[0.008]	[0.013]	[0.015]	[0.006]	[0.013]	[0.012]
Age	0.014***	0.056***	0.028***	-0,001	0.017***	0.011***
	[0.001]	[0.002]	[0.003]	[0.001]	[0.003]	[0.003]
=1 if Male	0,005	0.047***	-0,009	-0,002	-0.049***	-0,013
	[0.006]	[0.010]	[0.011]	[0.003]	[0.011]	[0.011]
Per Capita Household Income	0	0.000***	0.000***	0	0.000***	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
=1 if Urban	0.020***	0.061***	0.058***	-0,003	0.112***	0.034***
	[0.007]	[0.010]	[0.015]	[0.003]	[0.012]	[0.013]
Years of Education of Household Head	0.006***	0.030***	0.023***	0.003***	0.023***	0.006***
	[0.001]	[0.002]	[0.002]	[0.000]	[0.002]	[0.002]
=1 if Household Head is Female	0,002	0.030**	0.034***	-0,001	0.040***	0,008
	[0.009]	[0.013]	[0.012]	[0.004]	[0.012]	[0.011]
Observations	4656	7299	5032	11084	4477	1744
Chi2	202,04	1149,17	423,04	119,72	586,93	107,55

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 12B

Credit Dummy and Primary Education: Marginal Probabilities (Cont.)
All Households

Dependent Variable: Probability of Staying in Primary School	Nicaragua 1993	Peru 1997	Peru 1999	Peru 2002	Paraguay 2001
=1 if Household Received a Loan	-0,024	-0,014	-0,009	0,006	0,011
	[0.019]	[0.019]	[0.013]	[0.004]	[0.009]
Age	-0.008***	0.009***	0.006**	0.003***	0.009***
	[0.001]	[0.003]	[0.003]	[0.001]	[0.001]
=1 if Male	-0,007	0,006	0,009	-0,002	-0,006
	[0.005]	[0.011]	[0.011]	[0.003]	[0.004]
Per Capita Household Income	0	0	0	0.000**	0.000**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
=1 if Urban	0.021***	0,022	0.037**	0,007	0.015***
	[0.007]	[0.017]	[0.017]	[0.005]	[0.005]
Years of Education of Household Head	0.004***	0,002	-0,001	0.001*	0.008***
	[0.001]	[0.001]	[0.002]	[0.000]	[0.001]
=1 if Household Head is Female	-0,01	-0,051	0,001	0	0.009**
	[0.007]	[0.036]	[0.020]	[0.005]	[0.005]
Observations	3913	734	557	1777	6738
Chi2	108,64	29,07	15,8	59,36	321,4

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

We restrict the sample to poor households in Tables 13A and 13B. The positive and significant coefficients appear in Table 13A, which encompasses the cases of Bolivia (2002), Guatemala (2000), Haiti (2001), Nicaragua (2001) and Paraguay (2001). The marginal effect on the probability goes from a minimum of 4.3% in Paraguay to 10.6% in Nicaragua (1998). In these cases, once again, Age, Per capita household income, Urban residence and Years of education of the household head display, for the most part, positive and significant signs, while Female head does it in two of the five regressions.[9] The regressions in Table 13B show non significant credit effects (with the odd exception of a negative one in Nicaragua (1993)) and a wider variation in the sign and significance of the control set.

[9] We repeated the gender test run in the income regressions by adding the interaction between the credit variables and a dummy indicating whether the household head is a woman, but we could not reject the hypothesis that the statistical effect was nil.

Table 13A

Credit Dummy and Primary Education: Marginal Probabilities
Poor Households

Dependent Variable: Probability of Staying in Primary School	Bolivia 2002	Guatemala 2000	Haiti 2001	Nicaragua 1998	Paraguay 2001
=1 if Household Received a Loan	0.045***	0.102***	0.042**	0.106***	0.043***
	[0.013]	[0.029]	[0.016]	[0.023]	[0.015]
Age	0.019***	0.075***	0.031***	0.023***	0.017***
	[0.002]	[0.005]	[0.003]	[0.004]	[0.002]
=1 if Male	0.002	0.077***	-0.011	-0.066***	-0.006
	[0.010]	[0.019]	[0.012]	[0.016]	[0.010]
Per Capita Household Income	0	0.000***	0.000***	0.000***	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
=1 if Urban	0.005	0.033	0.058***	0.112***	0.020*
	[0.012]	[0.023]	[0.017]	[0.017]	[0.011]
Years of Education of Household Head	0.008***	0.038***	0.024***	0.024***	0.016***
	[0.002]	[0.004]	[0.002]	[0.003]	[0.002]
=1 if Household Head is Female	-0.004	0.006	0.035***	0.052***	0.005
	[0.016]	[0.029]	[0.013]	[0.019]	[0.012]
Observations	2524	2595	4522	2893	2428
Chi2	114.1	356.23	349.1	296.27	140.39

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 13B

Credit Dummy and Primary Education: Marginal Probabilities (Cont.)
Poor Households

Dependent Variable: Probability of Staying in Primary School	Mexico 2002	Nicaragua 1993	Nicaragua 2001	Peru 1997	Peru 1999	Peru 2002
=1 if Household Received a Loan		-0.083**	0,018	-0,039	0,023	-0,007
		[0.040]	[0.038]	[0.102]	[0.030]	[0.034]
Age	-0,001	-0.011***	0.021***	0.027***	0,006	0.010***
	[0.001]	[0.002]	[0.006]	[0.008]	[0.008]	[0.003]
=1 if Male	-0,005	-0,002	-0,037	0,002	0,034	-0,004
	[0.006]	[0.008]	[0.024]	[0.028]	[0.034]	[0.010]
Per Capita Household Income	0.000**	0	0	0	0	0.000**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
=1 if Urban	-0.018***	0.029***	0.078***	0,037		0.032***
	[0.007]	[0.010]	[0.027]	[0.033]		[0.010]
Years of Education of Household Head	0.006***	0.004***	0.014***	0,003	-0,006	0
	[0.001]	[0.002]	[0.004]	[0.004]	[0.005]	[0.001]
=1 if Household Head is Female	0,003	-0.019*	0,012		-0,074	0
	[0.008]	[0.011]	[0.025]		[0.123]	[0.026]
Observations	3907	2538	820	242	177	720
Chi2	51,09	69,17	41,29	17,07	5,47	32,42

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

We explore the relevance of the amount of credit received –as opposed to whether the household receive any credit, regardless of the amount- in Table 14 (all households) and Table 15 (poor households). The credit coefficient is significant only for Guatemala (2001) and Nicaragua (2001) for the whole sample, and for Guatemala and Nicaragua (1998) for the poor households. However, the economic impact is virtually negligible.

Table 14

Credit Amount and Primary Education: Marginal Probabilities
All Households

Dependent Variable: Probability of Staying in Primary School	Guatemala 2000	Nicaragua 2001	Nicaragua 1993	Nicaragua 1998	Peru 1997	Peru 1999	Peru 2002
Credit Amount	0.000***	0.000**	0	0	0	0	0
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Age	0.055***	0.015***	-0.008***	0.017***	0.006***	0.004***	0.004***
	[0.002]	[0.002]	[0.001]	[0.003]	[0.001]	[0.001]	[0.001]
=1 if Male	0.046***	-0.014	-0.007	-0.050***	0.008	0.011**	0
	[0.010]	[0.009]	[0.005]	[0.011]	[0.005]	[0.005]	[0.002]
Per Capita Household Income	0.000***	0.000***	0	0.000***	0.000***	0.000**	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
=1 if Urban	0.057***	0.084***	0.020***	0.116***	0.014**	0.01	0.013***
	[0.010]	[0.010]	[0.007]	[0.012]	[0.006]	[0.006]	[0.003]
Years of Education of Household Head	0.030***	0.016***	0.004***	0.024***	0.005***	0.003***	0.002***
	[0.002]	[0.002]	[0.001]	[0.002]	[0.001]	[0.001]	[0.000]
=1 if Household Head is Female	0.028**	0.027***	-0.01	0.040***	0.004	0.007	0.001
	[0.013]	[0.010]	[0.007]	[0.013]	[0.007]	[0.006]	[0.003]
Observations	7300	4567	3918	4484	5506	3044	14391
Chi2	1147.29	487.55	107.07	553.88	204.77	83.84	326.11

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 15

Credit Amount and Primary Education: Marginal Probabilities
Poor Households

Dependent Variable: Probability of Staying in Primary School	Guatemala 2000	Nicaragua 1998	Nicaragua 1993	Nicaragua 2001	Peru 1997	Peru 1999	Peru 2002
Credit Amount	0.000*	0.000**	0	0	0	0	0
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Age	0.074***	0.023***	-0.011***	0.022***	0.014***	0.008***	0.008***
	[0.005]	[0.004]	[0.002]	[0.004]	[0.003]	[0.003]	[0.001]
=1 if Male	0.076***	-0.067***	-0.002	-0.019	0.015	0.012	0.002
	[0.019]	[0.016]	[0.008]	[0.015]	[0.011]	[0.011]	[0.004]
Per Capita Household Income	0.000***	0.000***	0	0.000**	0.000*	0	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
=1 if Urban	0.031	0.115***	0.030***	0.118***	0.013	0.021*	0.020***
	[0.023]	[0.017]	[0.010]	[0.016]	[0.014]	[0.012]	[0.005]
Years of Education of Household Head	0.037***	0.025***	0.004**	0.026***	0.009***	0.006***	0.004***
	[0.004]	[0.003]	[0.002]	[0.003]	[0.002]	[0.002]	[0.001]
=1 if Household Head is Female	0.005	0.050***	-0.018*	0.041**	0.011	0.001	0.015***
	[0.029]	[0.019]	[0.011]	[0.017]	[0.016]	[0.016]	[0.005]
Observations	2595	2898	2539	2754	2627	1370	6872
Chi2	348.94	282.58	62.09	238.73	69.64	27.46	184.74

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

We repeat the previous experiments looking now at the decision to stay in secondary school. In Tables 16A and 16B we present the whole sample regressions for the credit dummy. Table 16A includes all the cases with a positive and significant estimate: Bolivia, Guatemala, Haiti, Mexico, Nicaragua (1998), Peru (1999), and Paraguay. The marginal effect reaches a minimum of 4.8% for Haiti and a maximum of 10.6% for Mexico. Among the controls, in all cases, Years of education of the household head and the Urban dummy appear as the most robust ones, along with Age, which now enters negatively (indicating that older teenagers drop out from school to start working). The gender of the household head does not seem to be influential on the secondary schooling decision.

For poor households, credit has a significantly positive impact in Haiti, Mexico, and Peru (1999), as shown in Tables 17A and 17B, with marginal probabilities of 5.7%, 18.2%, and 14.8%, respectively. The coefficients on the controls resemble those for the whole sample.

Table 16A

Credit Dummy and Secondary Education: Marginal Probabilities
All Households

Dependent Variable: Probability of Staying in Secondary School	Bolivia 2002	Guatemala 2000	Haiti 2001	Mexico 2000	Nicaragua 1998	Peru 1999	Paraguay 2001
=1 if Household Received a Loan	0.049***	0.086***	0.048**	0.106***	0.055*	0.077**	0.074***
	[0.015]	[0.025]	[0.019]	[0.030]	[0.029]	[0.038]	[0.026]
Age	-0.047***	-0.112***	-0.028***	-0.121***	-0.103***	-0.067***	-0.076***
	[0.004]	[0.006]	[0.005]	[0.004]	[0.007]	[0.013]	[0.004]
=1 if Male	0.029**	0.096***	-0,001	0,008	-0.061***	-0,024	0,013
	[0.012]	[0.016]	[0.015]	[0.010]	[0.020]	[0.038]	[0.012]
Per Capita Household Income	0	0.000***	0	0.000***	0	0	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
=1 if Urban	0.131***	0.249***	0.069***	0.029**	0.255***	0.099**	0.127***
	[0.014]	[0.017]	[0.018]	[0.012]	[0.021]	[0.049]	[0.014]
Years of Education of Household Head	0.017***	0.040***	0.015***	0.028***	0.046***	0.009*	0.030***
	[0.002]	[0.003]	[0.002]	[0.001]	[0.003]	[0.005]	[0.002]
=1 if Household Head is Female	0,02	0,028	0,019	-0,016	0,015	-0,043	0,015
	[0.015]	[0.022]	[0.016]	[0.014]	[0.023]	[0.060]	[0.014]
Observations	2956	4337	2898	7452	2886	311	4384
Chi2	461,79	1175,37	127,39	1691,92	800,85	49,08	859,38

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 16B

Credit Dummy and Secondary Education: Marginal Probabilities (Cont.)
All Households

Dependent Variable: Probability of Staying in Secondary School	Nicaragua 1993	Nicaragua 2001	Peru 1997	Peru 2002
=1 if Household Received a Loan	-0,021	-0,026	0,039	0,043
	[0.053]	[0.036]	[0.035]	[0.026]
Age	-0.098***	-0.086***	-0.078***	-0.062***
	[0.007]	[0.010]	[0.012]	[0.007]
=1 if Male	-0,026	-0.062**	0,002	0.080***
	[0.019]	[0.026]	[0.032]	[0.020]
Per Capita Household Income	0	0.000*	0	0
	[0.000]	[0.000]	[0.000]	[0.000]
=1 if Urban	0.261***	0.109***	0,032	0.061**
	[0.022]	[0.031]	[0.041]	[0.024]
Years of Education of Household Head	0.020***	0.023***	0.017***	0.010***
	[0.003]	[0.004]	[0.004]	[0.003]
=1 if Household Head is Female	-0,024	0.051*	-0,024	-0,02
	[0.021]	[0.027]	[0.045]	[0.030]
Observations	2528	1140	482	1100
Chi2	512,91	167,8	84,27	133,39

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 17A

Credit Dummy and Secondary Education: Marginal Probabilities
Poor Households

Dependent Variable: Probability of Staying in Secondary School	Haiti 2001	Mexico 2000	Peru 1999
=1 if Household Received a Loan	0.057***	0.182***	0.148**
	[0.021]	[0.061]	[0.066]
Age	-0.029***	-0.155***	-0.050**
	[0.006]	[0.008]	[0.025]
=1 if Male	0,004	0.060***	0,046
	[0.017]	[0.021]	[0.075]
Per Capita Household Income	0.000***	0	-0,001
	[0.000]	[0.000]	[0.000]
=1 if Urban	0.077***	0.048**	0.242***
	[0.020]	[0.023]	[0.061]
Years of Education of Household Head	0.015***	0.029***	0,002
	[0.003]	[0.004]	[0.014]
=1 if Household Head is Female	0,013	-0,014	-0,228
	[0.017]	[0.029]	[0.196]
Observations	2536	2223	102
Chi2	106	478,99	19,38

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 17B

Credit Dummy and Secondary Education: Marginal Probabilities (Cont.)
Poor Households

Dependent Variable: Probability of Staying in Secondary School	Bolivia 2002	Guatemala 2000	Nicaragua 1993	Nicaragua 1998	Nicaragua 2001	Peru 1997	Peru 2002	Paraguay 2001
=1 if Household Received a Loan	0,049	0,07	-0,06	0,06	-0,062	-0.517**	0,083	0,098
	[0.032]	[0.052]	[0.083]	[0.041]	[0.072]	[0.205]	[0.097]	[0.072]
Age	-0.062***	-0.105***	-0.120***	-0.090***	-0.084***	-0.137***	-0.064***	-0.108***
	[0.007]	[0.011]	[0.009]	[0.009]	[0.016]	[0.030]	[0.014]	[0.011]
=1 if Male	0.048**	0.111***	-0,029	-0.049*	-0,052	0,082	0.144***	0,027
	[0.021]	[0.030]	[0.026]	[0.026]	[0.044]	[0.084]	[0.043]	[0.029]
Per Capita Household Income	0	0.000*	0.000**	0.000**	0	0.001**	0	0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
=1 if Urban	0.161***	0.153***	0.259***	0.202***	0.108**	0,065	0,055	0.082**
	[0.021]	[0.036]	[0.027]	[0.027]	[0.050]	[0.112]	[0.046]	[0.035]
Years of Education of Household Head	0.026***	0.039***	0.017***	0.044***	0.029***	0.030**	0,01	0.034***
	[0.003]	[0.008]	[0.005]	[0.005]	[0.008]	[0.014]	[0.007]	[0.006]
=1 if Household Head is Female	0,008	0,01	-0,03	0,026	0,064	0,078	-0,028	-0,023
	[0.030]	[0.043]	[0.029]	[0.029]	[0.046]	[0.119]	[0.074]	[0.038]
Observations	1369	1165	1568	1715	469	123	377	1267
Chi2	241,54	169,08	314,22	344,09	55,6	36,52	37,81	186,21

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

The effects of the amount of credit appear in Table 18 (all households) and Table 19 (poor households). In neither of these cases do we observe an economically significant coefficient.

Table 18

Credit Amount and Secondary Education: Marginal Probabilities
All Households

Dependent Variable: Probability of Staying in Secondary School	Guatemala 2000	Nicaragua 2001	Nicaragua 1993	Nicaragua 1998	Peru 1997	Peru 1999	Peru 2002
Credit Amount	0	0	0	0	0	0.000*	0
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Age	-0.112***	-0.098***	-0.103***	-0.113***	-0.081***	-0.082***	-0.077***
	[0.006]	[0.007]	[0.007]	[0.007]	[0.005]	[0.006]	[0.002]
=1 if Male	0.096***	-0.025	-0.062***	-0.082***	0.007	-0.011	0.038***
	[0.016]	[0.019]	[0.020]	[0.019]	[0.013]	[0.017]	[0.007]
Per Capita Household Income	0.000***	0	0	0.000***	0	0	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
=1 if Urban	0.246***	0.261***	0.258***	0.198***	0.085***	0.112***	0.080***
	[0.017]	[0.022]	[0.021]	[0.020]	[0.016]	[0.020]	[0.009]
Years of Education of Household Head	0.041***	0.020***	0.047***	0.031***	0.019***	0.014***	0.009***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.002]	[0.002]	[0.001]
=1 if Household Head is Female	0.025	-0.024	0.015	0.066***	0.046***	-0.006	0.013
	[0.022]	[0.021]	[0.023]	[0.021]	[0.016]	[0.023]	[0.009]
Observations	4337	2529	2891	2855	3549	2063	9487
Chi2	1163.8	513.25	799.42	689.18	538.6	325.46	1336.35

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 19

Credit Amount and Secondary Education: Marginal Probabilities
Poor Households

Dependent Variable: Probability of Staying in Secondary School	Guatemala 2000	Nicaragua 2001	Nicaragua 1993	Nicaragua 1998	Peru 1997	Peru 1999	Peru 2002
Credit Amount	0	0	0	0	-0.000*	0.001	0
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]
Age	-0.106***	-0.120***	-0.090***	-0.115***	-0.084***	-0.087***	-0.079***
	[0.011]	[0.009]	[0.009]	[0.010]	[0.009]	[0.011]	[0.005]
=1 if Male	0.109***	-0.029	-0.050*	-0.102***	0.064***	0.024	0.075***
	[0.030]	[0.026]	[0.026]	[0.026]	[0.024]	[0.032]	[0.013]
Per Capita Household Income	0.000**	0.000**	0.000**	0	0	0	0.000**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
=1 if Urban	0.150***	0.260***	0.206***	0.187***	0.099***	0.122***	0.085***
	[0.036]	[0.027]	[0.027]	[0.028]	[0.028]	[0.035]	[0.014]
Years of Education of Household Head	0.038***	0.017***	0.044***	0.036***	0.030***	0.020***	0.016***
	[0.008]	[0.005]	[0.005]	[0.005]	[0.004]	[0.005]	[0.002]
=1 if Household Head is Female	0.003	-0.031	0.026	0.081***	0.061*	-0.011	0.018
	[0.042]	[0.029]	[0.029]	[0.030]	[0.032]	[0.048]	[0.018]
Observations	1165	1569	1717	1549	1391	777	3893
Chi2	167.32	314.27	343.54	309.19	207.12	99.52	479.91

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

4. Microsimulations

Having proved that the access to credit has a beneficial effect on the income and education attainment of poor households, we will conduct microsimulation exercises to assess the aggregate effect of increases in the amount of credit and in the number of poor borrowers.

4.1 Poverty Simulations

In line with our econometric specifications in Section 3, we have designed two different experiments, one for the credit dummy regressions and another for the credit amount regressions.[10]

In the first case, the estimations refer to a binary variable (whether the household received or not a loan), so we cannot clearly determine how much credit is necessary for the observed effect to take place.[11] Since we want to quantify the cost of these credit policies, we use in all cases, as a crude but yet realistic approximation, a loan size per household of US$500, the rounded average shown in Table 3. After computing the corresponding income increase based on the estimates of the previous section, we compared poverty before and after the implementation of the credit program, as well as the associated cost.

The credit dummy results are presented in the following table:

[10] In all cases, only those country cases with a statistically significant credit coefficient were considered.
[11] Let us recall that, even though credit is a inherently quantitative variable, we were forced to use the dummy variable because no credit amount data was surveyed in several of the household surveys in the sample.

Table 20

Change in Poverty: Simulation Effects (Credit Dummy)

	Bolivia 2002	Guatemala 2000	Haiti 2001
Poverty Reduction (in %) - US$2 Measure	**5.90**	**28.51**	**0.39**
Poverty Reduction (in %) - FGT1 Measure	**4.63**	**13.51**	**0.37**
Number of new loans	433,666	247,562	449,757
Annual Unit Cost (in US$)	500.0	500.0	500.0
Annual Total Cost (in million US$)	216.8	123.8	224.9
Annual Total Cost (% GDP)	2.8	0.6	6.0
Annual Total Cost (% Public Expenditure)	10.77	5.05	58.37

Sticking to the US$2 poverty line used throughout the paper, we find that poverty would go down by 5.9%, 28.5% and 0.4% in Bolivia, Guatemala and Haiti, respectively. We tested the sensitivity of the results by adopting the FGT1 measure, obtaining a noticeably different answer only in Guatemala, where the improvement drops to 13.5%. The annual total cost goes from US$124 million in Guatemala to US$225 million in Haiti. In terms of GDP and public expenditure, the burden is highest in Haiti and lowest in Guatemala.

We may want to know why credit is unable to cause a greater reduction in poverty and why the impact varies across countries. To this end, we present Table 21:

Table 21

Simulation Effects: Underlying Factors (Credit Dummy)

	Bolivia 2002	Guatemala 2000	Haiti 2001
Additional Annual Income needed to be non-poor (Median value, in US$)	898.1	818.4	838.9
Annual Household Labor Income increase after simulation (Median value, in US$)	91.5	1,195.3	49.3
Annual Per Capita Labor Income increase after simulation (Median value, in US$)	20.9	210.1	11.7
Percentage of total poor reached by the loan program	62.83	46.39	37.84
Credit regression coefficient (from Table 8 in the text)	0.274	1.247	0.197
Weekly working hours (Median value)	48.0	46.0	37.4
Household size	5.0	6.0	5.0

The percentage of individuals likely to be taken out of poverty depend on the following factors: (i) *How far their income is from the poverty line*: in this case the three countries are in a similar situation, with an annual deficit of US$ 800/900; (ii) *How much credit is granted*: from Table 20, we identify a first difference in favor of Guatemala, where the assumed household credit amounts to US$145 against values of US$85 and US$70 in Bolivia and Haiti, respectively -the difference being explained by the decision to extend a loan equal to 10% of median household income; (iii) *How many poor households receive credit*: since credit is targeted only to self-employed and entrepreneurs (but not to salaried workers that do not undertake personal productive projects), the potential poor population getting a loan ranges from 38% in Haiti to 63% in Bolivia, and (iv) *How much per capita labor income increases as a result of the credit program*: this, in turn, depends on how sensitive income is to credit, how many hours the household head works (recall that our dependent variable is the logarithm of the hourly labor income), and how many member the household has (as we are interested in individual poverty and thus on per capita household income). Here we detect the main source of disparity among the three cases: Guatemala's estimate is 6.3 times higher than that of Haiti –and 4.6 greater than Bolivia's- and the hours worked are 28.2% higher as well.

In the credit amount experiment, we took a different approach by assuming that all poor households with a self-employed or entrepreneur head receive enough credit to move out of poverty, with the income effect of credit taken from the estimates in Table 10 for the only significant estimate: Guatemala. This implies that each household gets different amounts according to how poor it is. As Table 22 shows, poverty diminishes by 48% in Guatemala. The median household credit is US$549, but with a wide dispersion across households. The annual total cost of this high impact program reaches US$190.1 millions, equivalent to 1% of GDP and 7.8% of public expenditure. This steeper cost is explained by both the higher unit cost and the larger number of poor households reached.

Table 22

Change in Poverty: Simulation Effects (Credit Amount)

	Guatemala 2000
Poverty Reduction (in %) - US$2 Measure	**48.00**
Number of new loans	276,045
Annual Unit Cost (in US$)	
Median	548.8
Maximum	4082.3
Minimum	0.0
Annual Total Cost (in million US$)	190.1
Annual Total Cost (% GDP)	1.0
Annual Total Cost (% Public Expenditure)	7.8

4.2 Education simulations

We now turn to the effects of credit on primary and secondary outcomes. Given our probit specification, the exercises will evaluate the increase in the average probability of staying at school once all poor households with children aged 6-17 get credit.[12]

The probability of staying in primary school, as shown in Table 23, rises by between 3.5 percentage points in Haiti to 8.9 percentage points in Nicaragua (1998).[13] In Table 24, we restrict the recipient households to those whose children do not currently attend school, with a noticeable drop in the probability variation. The average financial cost, measured by GDP points, moves between 0.9% in the restricted sample and 3.4% in the broad sample. Regarding secondary school, from Table 25, the average probability increases by 4.8, 15.7 and 14.3 percentage points in Haiti (2001), Mexico (2002) and Peru (1999), respectively. Again, the impact shrinks when the sample is restricted only to dropouts´ households. The cost of the program amounts, on average, to 0.5% and 1.6% of GDP in the narrow and the broad sample, respectively, but varies significantly across countries in linear relation with the number of households covered.

Table 23

[12] The nature of the exercise is close to Orbeta and Alba (1999), Kuenning et al. (2005) and Filmer and Schady (2006), who assess the impact of different education subsidy programs.

[13] Using the credit amount regressions for Guatemala and Nicaragua (1998), we tested whether our hypothetical loan of US$500 actually predicts the increase in probability shown in Table 23 for these countries. The results roughly confirmed the consistency between the dummy and the available (statistically significant) amount exercises.

Primary Education: Simulation Effects

New credit provided to all poor households with children aged 6-12

	Bolivia 2002	Guatemala 2000	Haiti 2001	Nicaragua 1998	Paraguay 2001
Average probability before simulation	91.3	64.5	77.2	75.4	91.9
Average probability after simulation	96.0	73.1	80.8	84.3	96.7
Change in probability	**4.7**	**8.6**	**3.5**	**8.9**	**4.8**
Number of new credits	408,011	346,428	481,202	247,285	154,263
Annual unit cost (in US$)	500.0	500.0	500.0	500.0	500.0
Annual total cost (in million US$)	204.0	173.2	240.6	123.6	77.1
Annual Total Cost (% GDP)	2.6	0.9	6.4	6.0	1.1
Annual Total Cost (% Public Expenditure)	10.1	7.1	62.5	16.7	6.1

Table 24

Primary Education: Simulation Effects

New credit provided to all poor households with children aged 6-12 not attending school

	Bolivia 2002	Guatemala 2000	Haiti 2001	Nicaragua 1998	Paraguay 2001
Average probability before simulation	91.3	64.5	77.2	75.4	91.9
Average probability after simulation	91.8	67.8	78.3	77.8	92.6
Change in probability	**0.6**	**3.3**	**1.0**	**2.5**	**0.6**
Number of new credits	57,227	170,887	141,979	70,305	22,565
Annual unit cost (in US$)	500.0	500.0	500.0	500.0	500.0
Annual total cost (in million US$)	28.6	85.4	71.0	35.2	11.3
Annual Total Cost (% GDP)	0.4	0.4	1.9	1.7	0.2
Annual Total Cost (% Public Expenditure)	1.4	3.5	18.4	4.7	0.9

Table 25

Secondary Education: Simulation Effects

New credit provided to all poor households with children aged 13-17

	Haiti 2001	Mexico 2002	Peru 1999
Average probability before simulation	77.8	64.4	76.9
Average probability after simulation	82.6	80.2	91.2
Change in probability	**4.8**	**15.7**	**14.3**
Number of new credits	336,378	1,870,289	70,380
Annual unit cost (in US$)	500.0	500.0	500.0
Annual total cost (in million US$)	168.2	935.1	35.2
Annual Total Cost (% GDP)	4.5	0.1	0.1
Annual Total Cost (% Public Expenditure)	43.7	0.6	0.3

Table 26

Secondary Education: Simulation Effects

New credit provided to all poor households with children aged 13-17 not attending school

	Haiti 2001	Mexico 2002	Peru 1999
Average probability before simulation	77.8	64.4	76.9
Average probability after simulation	79.1	71.4	82.5
Change in probability	**1.3**	**6.9**	**5.5**
Number of new credits	96,334	841,484	26,870
Annual unit cost (in US$)	500.0	500.0	500.0
Annual total cost (in million US$)	48.2	420.7	13.4
Annual Total Cost (% GDP)	1.3	0.1	0.0
Annual Total Cost (% Public Expenditure)	12.5	0.3	0.1

Conclusions

This study used for the first time household survey data in Latin America to investigate the degree and effects of the access to credit on the income and education of poor households. With this goal in mind, we run multivariate regressions to estimate the impact of the credit to the poor on their labor income and on the probability of their children to stay at both primary and secondary school. Afterwards, based on these results, we simulate alternative credit policies. The sample covers different years since the 1990s of the following countries: Bolivia, Guatemala, Haiti, Mexico, Nicaragua, Peru, and Paraguay.

The data showed that less than 10% of poor households have access to credit in the sample, and exploratory statistics suggest a positive link of credit with income and education attainment. However, regression analyses, much in line with the available evidence, provided mixed results: while no negative effects are identified, positive and significant loadings are found in several, but not all cases. Also, the estimates vary across country cases. In turn, gender effects, whereby female household heads appear to make more efficient credit allocations, do not emerge in the present investigation.

One critical issue to be considered in making sense of our results is that our database only provides information on whether poor households have obtained credit, and so a categoric verdict on how good credit is, especially in relation to labor income, is still pending. Although household surveys have the apparent advantages of any large sample and provides a valuable characterization of the borrower, we ideally would like to have additional information on the lender and the loan contract. For instance, the outcome may change according to whether the lender is a bank or a microfinance institution, and whether it is a public or private organization, as incentives and selection and monitoring technologies may be radically different –the fact that some lenders provide other services to the borrower, such as payment and insurance services and technical assistance during the project´s life should not be disregarded. When it comes to contractual aspects, the size, interest rate and term of the loan, as well as its covenants and application requirements, may also influence the loan´s return. At a more aggregate level, sectoral and macroeconomic performance should also be taken into account.[14] For future research agenda, it would be desirable to check the robustness of our results once some of these factors are examined. The recommendations on the design of microcredit programs would also be more focused.

For the statistically significant regressions, we simulated alternative credit policies targeted to the poor that delivered a reasonable cost-benefit balance. Regarding the impact on labor income and the program cost, the most promising case is Guatemala. As for education, the increase in the probability of completing the secondary school is on average higher than for primary school, and the corresponding cost is lower as well. In a nutshell, it seems that microcredit might be a relatively powerful but still limited tool for meeting the MDGs. This should come as no surprise: credit can be instrumental in reducing poverty and improving educational attainment only provided some prior conditions are met with respect to household preferences, skills, and financial literacy and practices. Just as an example, a loan will be much more likely to have some positive impact if the household head is educated and does not display moral hazard-prone myopia. Therefore, microcredit schemes should not be thought as a substitute but as a complement to other long-term policies.

In any case, as far the estimated costs are concerned, they do not seem extraordinarily high in most cases. This claim is reinforced once we take into account that loans are supposed to be repaid. Of course, this does not mean that any initiative will be cost-free at all. The channeling of funds from international and national donors and intermediaries to the final borrowers can be very expensive, which adds to the expected losses from defaulting loans. The selection and incentive mechanisms for the financial institutions ultimately in charge of the credit extension process is not a minor issue. For example, public institutions in some countries seem to perform worse than private microfinance organizations as a result of distorted incentives and the client´s perception that government programs are poorly enforced or that their loans are straight subsidies not involving a financial obligation.

[14] In our defense, we must say that many previous contributions, due to similar information constraints, include even smaller control sets as ours.

Perhaps the most potent and long-lasting impact of a microcredit program is the behavioral change that participation may bring with it. The interaction with other prospective (or previously successful) entrepreneurs, the access to technical assistance to prepare and implement business plans, and the possibility to create direct ties with formal and informal financial intermediaries once the original program has finished are positive, enduring effects derived from microfinance policies.[15] One visible and likely effect of this sort is an increased awareness about the returns of schooling and the benefits of maintaining a good credit record. From this perspective, microfinance can decisively help in the quest for the MDGs, even when these effects are difficult to pick up in conventional econometric research.

[15] Microcredit will most probably have these lasting behavioral effects when borrower participation in the program stretches for a period long enough, say, no less than one or two years. In the same vein, interaction should be promoted and kept as a priority practice by the microfinance institution.

References

Angrist J. and A. Krueger (2001), "Instrumental variables and the search for identification: From supply and demand to natural experiments", NBER Working Paper, No. 8456, September.

Barnes C. (2001), "Microfinance Program Clients and Impacts: An Assessment of Zambuko Trust, Zimbabwe", USAID.

Bebczuk R. (2003a), Asymmetric Information in Financial Markets: Introduction and Applications, Cambridge University Press, UK.

Bebczuk R., J. Fanelli, and J. Pradelli (2003b), "Financial Constraints Facing Firms in Argentina", IDB Working Paper No. 516.

Beck T., A. Demirguc-Kunt and R. Levine (2004), "Finance, Inequality, and Poverty: Cross-Country Evidence", NBER Working Paper, No. 10979, December.

Behrman J. and R. Rozenweig (2002), "Does Increasing Women's Schooling Raise the Schooling of the Next Generation?", American Economic Review, Vol. 92, 323-334.

Bound J., D. Jaeger, and R. Baker (1995), "Problems with Instrumental Variables Estimation When the Correlation Between the Instruments and the Endogenous Variable is Weak", Journal of the American Statistical Association, Vol. 90, No. 430, 443-450.

Clarke G., L. Xu and H. Zou (2003), "Finance and Income Inequality: Tests of Alternative Theories", World Bank Policy Research Paper, No. 2984.

Filmer D. and N. Schady (2006), "Getting Girls into School: Evidence from a Scholarship Program in Cambodia", World Bank Policy Research No. 3910, May.

Gasparini L., F. Gutiérrez, A. Támola, L. Tornarolli and G. Porto (2005), "Finance and Credit Variables in Household Surveys of Developing Countries", CEDLAS Working Paper, Universidad Nacional de La Plata.

Gasparini L. (2001), "Inequidad en el acceso a la educación secundaria y superior en la Argentina", INDEC, Serie Fondo de Investigaciones.

Heckman J., L. Lochner and P. Todd (2003), "Fifty Years of Mincer Earnings Regressions", NBER Working Paper No. 9732.

Honohan P. (2004), "Financial Development, Growth, and Poverty: How Close Are the Links?", in Ch. Goodhart (ed.), Financial Development and Growth: Explaining the Links, Palgrave, forthcoming.

IDB (1999), Facing Up to Inequality in Latin America, IPES 1998/1999.

Khandker S. (2003), "Micro-Finance and Poverty: Evidence Using Panel Data from Bangladesh"*, World Bank Policy Research Working Paper No. 2945.*

Khandker S. and M. Pitt (1998), "The Impact of Group-Based Credit Programs on Poor Households in Bangladesh: Does the Gender of Participants Matter?", *Journal of Political Economy*.

Khandker S. (1998), *Fighting Poverty with Microcredit: Experience in Bangladesh*, Oxford University Press.

Kuenning M., A. Kassouf, A. Fava and A. Almeida (2005), "The impact of school quality and school incentive programs on children´s schooling and work in Brazil", mimeo, University of Illinois at Urbana-Champaign.

Maldonado J. (2005), "The Influence of Microfinance on the Education Decisions of Rural Households: Evidence from Bolivia", Documento CEDE 2005-46, Universidad de los Andes.

Marchionni M. and W. Sosa Escudero (1999), "Los determinantes de la decisión de escolarización", Documento de Trabajo, Maestría en Finanzas Públicas Provinciales y Municipales, Universidad Nacional de La Plata.

Meyer R. (2002), "Track Record of Financial Institutions Assisting the Poor in Asia", ADB Institute Research Paper No.49, Asian Development Bank.

Orbeta A. and M. Alba (1999), "A Probit Model of School Attendance for Children 7 to 14 years old", MIMAP Research Paper No. 20.

Panjaitan-Drioadisuryo R and K. Cloud (1999), "Gender, self-employment and microcredit programs: An Indonesian case study", Quarterly Review of Economics and Finance, Vol. 39.

Pitt M., S. Khandker and J. Cartwright (2003), "Does Micro-Credit Empower Women? Evidence from Bangladesh", *World Bank Policy Research Working Paper No. 2998*.

Pitt M. and S. Khandker (1998), "The Impact of Group-Based Credit Programs on Poor Households in Bangladesh: Does the Gender of Participants Matter?", *Journal of Political Economy,* Vol. 106, No. 5, 958-996.

Sharma M. (2000), "Impact of Microfinance on Poverty Alleviation: What Does Emerging Evidence Indicate?", Policy Brief No.2, International Food Policy Research Institute, March.

Simtowe F., M. Zeller and A. Phiri (2006), "Determinants of Moral Hazard in Microfinance: Empirical Evidence from Joint Liability Lending Schemes in Malawi", mimeo, Center for Development Research, University of Bonn.