Labor market effects of improved access to credit among the poor: evidence from Cape Verde

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Abstract

In the context of a collective household choice model, we show that the effects of improved credit access on search intensity by the unemployed are heterogeneous across households and dependent on the within-household bargaining power of the unemployed. We find empirical support for the predictions of our model using a household survey conducted by the authors in Cape Verde. These findings have important implications for the optimal design of microfinance programs, in particular concerning the targeting of loans and the use of microfinance as an instrument to support improved labor market outcomes.

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1 Introduction

How does improved access to credit by poor households affects the labor market behavior of the individuals in the household and, in particular, search effort by the unemployed? We ask this question in the context of a model of collective household behavior. We consider multi-member households in which at least one member is unemployed and another member is an entrepreneur. The household invests all its net-worth in the entrepreneurial activity. Improved access to credit allows the household to invest in technology adoption, raising the return to the household's net-worth. We show that the impact on job search effort by the unemployed depends crucially on the intra-household distribution of bargaining and decision power.

Targeting benefits to a particular household member (for example to women instead of men) has been shown to have important consequences on the ultimate use of the corresponding resources. Blundell et al. (2005) label this the targeting view. The upshot is that to analyse the way in which individual behavior is affected by improved access to credit, we need to model the household as a collective of individuals rather than as a single unit. Thus, we develop a model of job search and entrepreneurship that characterizes intra-household allocations within a bargaining framework, as a Pareto efficient outcome. This framework can address how the distribution of bargaining power affects consumption and effort choices within the household. The latter is crucial to understand the labor market implications of improved access to credit by poor families.

In particular, the impact of improved access to credit on search intensity by the unemployed is shown to be affected by two competing effects. Having access to finance may raise search intensity, as it raises the return to the household's net-worth and, by finding a job, the unemployed worker helps increasing the household's net-worth. But at the same time, households with access to finance experience a positive income effect that lowers the incentive to search. Which effect dominates depends on the bargaining power of the unemployed worker. We prove that when the bargaining power of the unemployed member of the household is high the positive net-worth effect is relatively stronger and, hence, improved access to credit is more likely to improve the labor market outcomes of the household members.

We test the predictions of our model using a tailored household survey conducted by the authors in Cape Verde (an island country in the west coast of Africa) in 2013, as part of a study commissioned by the United Nations Development Program (UNDP). The focus of the survey was the impact of microfinance loans on household outcomes and, in particular, labor market outcomes. The empirical tests that we carry out provide robust support for our theoretical predictions. The effects of improved credit access on search intensity by the unemployed are found to be heterogeneous across households and dependent on the within-household bargaining power of the unemployed. In particular, we find that unemployed workers with high bargaining power, increase their search intensity if they live in a household with access to microfinance. Instead, access to microfinance lowers search intensity among unemployed workers with low bargaining power. We use as exogenous proxies for the individual bargaining power the gender of the unemployed worker, schooling, household size and a dummy variable for whether the unemployed is the head of household.

Since expenditure is often observed at the household level, tests of intra-household allocation models are often inferential, aimed at determining whether household expenditure shares on various goods differ based on who controls income. In an early contribution, Thomas (1990) shows that male and female non-labor incomes (used as proxies for within household decision power) have different impact on children health. Browning et al. (1994) look at how intrahousehold sharing is affected by factors such as relative ages and incomes by focusing on expenditure in items which are gender-specific like clothing. Looking at data from South Africa, Duflo (2000) finds that the consequences of household revenue windfalls on child nutrition strongly depend on the gender of the recipient. In the context of testing models of collective household choice, looking at labor market behaviour and in particular our focus on the search effort by the unemployed, is attractive because leisure is a private good.

Job search has been shown to be affected by wealth but also cash-on-hand and credit constraints. Lentz and Tranas (2005) show that job search is monotonically decreasing with wealth when the utility function is separable in consumption and search effort. Furthermore, search effort exhibits positive unemployment duration dependence as a direct implication of the negative relationship between search effort and wealth. Card et al. (2007) estimate the excess sensitivity of job search behavior to cash-on-hand using sharp discontinuities in eligibility for severance pay and extended unemployment insurance in Austria. Their findings provide important implications about the efficiency costs of social insurance programs. Our analysis offers important insights on normative issues concerning the design of optimal microfinance programs and, in particular, the targeting of micro loans. Improved access to credit by the poor made possible by microfinance raises the returns to net-worth and consequently affects labor market outcomes. But loans should be targeted to families in which the unemployed workers have relatively high bargaining power.

The paper proceeds as follows. Section 2 presents a model of job search within a collective household choice framework and derives the main proposition to be tested. Section 3 describes the survey design and the data. Section 4 outlines our estimation strategy and identification assumptions. Section 5 presents the empirical results. Lastly, Section 6 concludes.

2 Credit and Labor Search: a theoretical framework

We examine the effects of improved access to credit on labor market outcomes, in particular search intensity by the unemployed. Our analysis is reminiscent of the study of sensitivity of labor market search effort to cash-on-hand by Card et al. (2007).

The purpose of the empirical work is to test the predictions from a model of job search and household collective behavior, in an environment with search frictions and finance constraints. We develop a simple collective model of household choice with two periods, date 0 and date 1. A household consists of a match between an entrepreneur and a worker. The latter starts date 0 unemployed. The labor market is characterized with frictions and the unemployed worker must choose search intensity.

There are two types of households. Those with access to credit and those without access. Households with access to credit are able to finance an investment of size K, that raises the return to the household's entrepreneurial activity. Instead, creditless households do not have enough net-worth to purchase the investment and, hence, enjoy a lower return on their entrepreneurial activity, set to zero without loss of generality.

Job Search with Collective Household Choice

We posit a collective model of household behavior by requiring the outcomes of household choice to be Pareto efficient.[1] This model can be implemented by assuming that the household has an objective function which is a weighted sum of the individuals' private utility functions; the weights may be interpreted as the bargaining power of each household member as, for example, in Anderson and Baland (2002) and Blundell et al. (2005). Both household members enjoy utility from consumption, and the unemployed worker dislikes searching for a job.

Let t denote the household type, with $t = 0$ for households without access to credit, and $t = 1$ for households with access to credit (the treatment group). The household must choose the date 0 search effort of the unemployed worker, $S(t)$, and the date 1 household's contingent consumption allocations

$$\begin{aligned} \mathbb{C}_e(t) &= \left(\widehat{C}_e(t), C_e(t)\right), \\ \mathbb{C}_n(t) &= \left(\widehat{C}_n(t), C_n(t)\right), \end{aligned} \tag{1}$$

[1] See, for example, Chiappori (1992).

where $\mathbb{C}_e(t)$ is the allocation in the event that the search is successful while $\mathbb{C}_n(t)$ is the allocation in the event that the the worker stays unemployed; $\widehat{C}$ is the consumption of the entrepreneur and C that of the worker.

We normalize $S(t)$ to equal the probability of finding a job by the unemployed worker and always assume an interior solution, $S(t) \in (0,1)$. Following the work by Card et al. (2007), we adopt three key simplifying assumptions: if the search is successful, the individual earns wage W at the end of date 0; there is a single wage rate; utility is separable in consumption and search effort, represented by the utility function

$$\begin{aligned}\mathbf{J}(S, \mathbb{C}_e, \mathbb{C}_n; t) = \alpha v(S(t)) + S\left[u\left(\widehat{C}_e(t)\right) + \alpha u\left(C_e(t)\right)\right] \\ + (1-S)\left[u\left(\widehat{C}_n(t)\right) + \alpha u\left(C_n(t)\right)\right],\end{aligned} \tag{2}$$

where we have normalized to one the weight placed on the entrepreneur's utility so that $\alpha > 0$ represents the relative bargaining power of the unemployed worker. Function $v(\bullet)$, capturing the disutility from search, is decreasing and concave, and $u(\bullet)$ is assumed to be increasing, concave and homothetic, and to satisfy the condition $u'''(\bullet) \geq 0$.

At the end of the second period, when consumption takes place, the household total resources, $Y(t)$, are given by

$$\begin{cases} Y_e(1) = RK - (1+r)(K - A - W) & \text{if household j has loan and individual i finds job;} \\ Y_n(1) = RK - (1+r)(K - A) & \text{if household j has loan and individual i does not find job;} \\ Y_e(0) = A + W & \text{if household j does not have loan and individual i finds job;} \\ Y_n(0) = A & \text{if household j does not have loan and individual i does not find job;} \end{cases} \tag{3}$$

where A are the household's financial assets.

The problem solved by the household is represented by the program

$$\begin{gathered}\max_{S, \mathbb{C}_e, \mathbb{C}_n} \mathbf{J}(S, \mathbb{C}_e, \mathbb{C}_n; t), \\ \text{subject to } \widehat{C}(t) + C(t) \leq Y(t).\end{gathered} \tag{4}$$

The optimality condition solving problem (4) are

$$-\alpha v'\left(S\left(t\right)\right)=\left[u\left(\widehat{C}_{e}\left(t\right)\right)+\alpha u\Big(C_{e}\left(t\right)\Big)\right]-\left[u\left(\widehat{C}_{n}\left(t\right)\right)+\alpha u\Big(C_{n}\left(t\right)\Big)\right],\quad(5)$$

$$u'\left(\widehat{C}_{e}\left(t\right)\right)=\alpha u'\Big(C_{e}\left(t\right)\Big),\quad(6)$$

$$u'\left(\widehat{C}_{n}\left(t\right)\right)=\alpha u'\Big(C_{n}\left(t\right)\Big).\quad(7)$$

Since $u\left(\bullet\right)$ is homothetic and concave, conditions (6) and (7) combined imply

$$\frac{\widehat{C}_{e}\left(1\right)}{C_{e}\left(1\right)}=\frac{\widehat{C}_{n}\left(1\right)}{C_{n}\left(1\right)}=\frac{\widehat{C}_{e}\left(0\right)}{C_{e}\left(0\right)}=\frac{\widehat{C}_{n}\left(0\right)}{C_{n}\left(0\right)}=f\left(\alpha\right)>0,\quad(8)$$

with $f'\left(\alpha\right)<0$. It follows that the optimality condition (5) can be expressed as

$$-v'\left(S\left(t\right)\right)=\hat{u}\left(C_{e}\left(t\right)\right)-\hat{u}\left(C_{n}\left(t\right)\right),\quad(9)$$

where $\hat{u}_{i}\left(C\right)=u\left(C\left(t\right)f\left(\alpha\right)\right)+\alpha u\left(C\left(t\right)\right)$. It is easy to verify that for any fixed $\alpha>0$, if the function $u\left(\bullet\right)$ is increasing, concave and has positive third derivative, these properties are inherited by the function $\hat{u}_{i}\left(\bullet\right)$.

Finance and Search Intensity

The impact that having access to micro-loans has on search intensity turns out to be ambiguous, as there are two competing effects of finance on job search intensity. Having access to finance may raise search intensity, as it raises the return to the household's net-worth. But at the same time, households with access to finance experience a positive income effect that lowers the incentive to search. The overall effect depends on the concavity of the utility function.

For a given bargaining power parameter α, it follows from condition (8) and the household budget constraint that

$$C\left(t\right)=\left(1+f\left(\alpha\right)\right)^{-1}Y\left(t\right).\quad(10)$$

Define the function

$$\Delta\left(C_{e},C_{n};t\right)=\hat{u}\left(C_{e}\left(t\right)\right)-\hat{u}\left(C_{n}\left(t\right)\right).\quad(11)$$

To identify the two competing effects of finance on job search intensity, take the first-order Taylor expansion of $\Delta\left(C_{e},C_{n};t\right)$ around $\left(1+f\left(\alpha\right)\right)^{-1}Y_{n}\left(t\right)$ and impose the budget constraint (10). This yields

$$\widetilde{\Delta}(\alpha;t)=\begin{cases}\hat{u}'\left((1+f(\alpha))^{-1}Y_n(1)\right)\left[(1+f(\alpha))^{-1}(1+r)W\right], & t=1\\ \\ \hat{u}'\left((1+f(\alpha))^{-1}Y_n(0)\right)\left[(1+f(\alpha))^{-1}W\right], & t=0\end{cases} \tag{12}$$

Ignoring higher-order terms, the optimality conditions for the choice of search intensity can be expressed as

$$-\alpha v'(S(t))=\widetilde{\Delta}(\alpha;t). \tag{5$'$}$$

Thus, the effect of treatment on search intensity is given by

$$\frac{dS(t)}{dt}=-\frac{d\widetilde{\Delta}(\alpha;t)/dt}{\alpha v''(S(t))}, \tag{13}$$

which is ambiguously signed because of $\left(d\widetilde{\Delta}(\alpha;t)/dt\right)$. On the one hand,

$$(1+f(\alpha))^{-1}(1+r)W>(1+f(\alpha))^{-1}W, \tag{14}$$

which raises $\widetilde{\Delta}(\alpha;1)$ relative to $\widetilde{\Delta}(\alpha;0)$, representing the net-worth effect. But, on the other hand, because $u''(\bullet)<0$ and $Y_n(1)>Y_n(0)$, we have that

$$\hat{u}'\left((1+f(\alpha))^{-1}Y_n(1)\right)<\hat{u}'\left((1+f(\alpha))^{-1}Y_n(0)\right), \tag{15}$$

which lowers $\widetilde{\Delta}(\alpha;1)$ relative to $\widetilde{\Delta}(\alpha;0)$, representing the income effect; Since $v''(\bullet)<0$, if the net-worth effect dominates we have that $S(1)>S(0)$ while the opposite is true if the income effect dominates.

While the impact of improved finance on search intensity is ambiguous, the model delivers a sharp prediction concerning the relationship between the unemployed worker's bargaining power, α, and the relative strengths of the net-worth and income effects.

To see this, first notice that

$$(1+f(\alpha))^{-1}(1+r)W-(1+f(\alpha))^{-1}W=(1+f(\alpha))^{-1}rW \tag{16}$$

which is increasing in α, since $f'(\alpha)<0$. Thus, the positive net-worth effect is increasing in the bargaining power of the unemployed worker. Instead, the strength of the income effect is decreasing in bargaining power, since

$$\begin{aligned}\partial\left[\frac{\hat{u}'\left((1+f(\alpha))^{-1}Y_n(1)\right)}{\hat{u}'\left((1+f(\alpha))^{-1}Y_n(0)\right)}\right]\frac{1}{\partial\alpha}&=\left[\frac{-f'(\alpha)}{(1+f(\alpha))^2}\right]\times\\ &\left[\frac{\hat{u}''(C_n(1))\,\hat{u}'(C_n(0))\,Y_n(1)-\hat{u}''(C_n(0))\,\hat{u}'(C_n(1))\,Y_n(0)}{\hat{u}'(C_n(0))^2}\right]>0.\end{aligned} \tag{17}$$

The later must be positive, because $f'(\alpha) < 0$ and $C_n(0) < C_n(1)$, and $\hat{u}''(\bullet) < 0$ and $\hat{u}'''(\bullet) \geq 0$, implying that $u'(C_n(0)) \geq u'(C_n(1))$ and $u''(C_n(0)) \leq u''(C_n(1))$. The upshot is that the negative income effect is weaker when the bargaining power of the unemployed worker is high.

We, therefore, establish the following proposition:

Proposition 1. *The effects of improved credit access on search intensity by the unemployed are heterogeneous across households and dependent on the within-household bargaining power of the unemployed. In particular:*

1. *Being part of a household with access to a loan exerts two competing effects on the individual search intensity: the loan raises the return to job search, since finding a job raises the household's net-worth, which is more valuable when the household has access to credit; but, receiving a loan implies a positive income effect which discourages job search. The overall effect on search intensity of an unemployed individual is ambiguous.*

2. *All else equal, the search intensity of an unemployed individual who is in a household receiving a loan, relative to the search intensity of the same individual if her household did not receive the loan, is increasing in the bargaining power of the unemployed worker:*

$$\frac{\partial\Big(S(1) - S(0)\Big)}{\partial\alpha} > 0. \tag{18}$$

3 Data and Survey Design

We use data from a household survey undertaken in the Santiago island of Cape Verde in 2013 as part of a broader project evaluating the impact of microfinance in the island country. Based on information from the main microfinance institutions (MFI) in Santiago, we identified areas where microfinance clients are more likely to reside. The original sample contains 600 households and was constructed using a stratified random sampling technique. Because job and business opportunities differ considerably between urban and rural settings, the principal dimension of stratification was whether households live in an urban or rural area. In the capital city of Praia, we chose 10 neighborhoods based on their relevance for microfinance. We excluded the wealthier neighborhoods and the ones in which the employment rate is well above the national average reported by the 2010 Census. As primary sampling unit, we then randomly selected 20 census districts (CD) overlapping those neighborhoods.[2] Each CD contains 180 dwellings (and

[2]CD are precisely delimited geographical zones, drawn for the 2010 National Census and covering the whole national territory.

Table 1: Characteristics of households with unemployed members

	Household access to lending							
	1: no loan		2: MFI loan		3: bank loan		4: full sample	
# of households	226		56		43		348	
Rural household	0.30	(0.03)	0.29	(0.06)	0.26	(0.07)	0.29	(0.03)
Household size	5.29	(0.17)	6.14**	(0.35)	6.42**	(0.43)	5.59	(0.15)
# of children 15 or younger	1.55	(0.10)	2.04**	(0.21)	1.51	(0.22)	1.63	(0.08)
Head is woman	0.51	(0.03)	0.59	(0.07)	0.33**	(0.07)	0.50	(0.03)
Age of head	49.28	(1.08)	48.46	(1.77)	52.58	(2.16)	49.58	(0.86)
Head's schooling	4.69	(0.27)	4.14	(0.51)	5.58	(0.63)	4.72	(0.22)
Spouse's schooling	4.73	(0.46)	5.15	(0.64)	4.79	(0.67)	4.81	(0.33)
Head is unemployed	0.35	(0.03)	0.29	(0.06)	0.16**	(0.06)	0.31	(0.03)
Spouse is unemployed	0.26	(0.03)	0.18	(0.05)	0.47***	(0.08)	0.27	(0.02)
# of members self-employed	0.31	(0.04)	0.57***	(0.09)	0.28	((0.09)	0.35	(0.03)
# of members unemployed	1.00	(0.06)	1.09	(0.12)	1.26	(0.16)	1.05	(0.05)
# of income sources	1.69	(0.08)	1.80	(0.15)	2.21***	(0.21)	1.78	(0.07)
Poverty headcount ratio	0.52	(0.03)	0.57	(0.07)	0.28***	(0.07)	0.50	(0.03)

Standard errors in parentheses, *p<0.10, ** p<0.05, *** p<0.01.

so approximately 180 households). Concerning the stratum of rural households, we chose three representative areas and randomly selected 10 CD. Finally, in each CD, both urban and rural, we randomly selected 20 households using maps prepared by the National Statistics Institute. Because of the CD design, this procedure made sure that each household had approximately the same probability of being interviewed.[3]

Two restrictions are imposed on the original sample of surveyed households. Since, we are interested in the effects of improved access to credit on the search behavior of unemployed members of the household, we drop households that have no unemployed members aged between 16 and 65 years old. Second, the survey asks if the household has received any kind of loan in the past (either from a bank or from an MFI). Thus, our sample contains four types of household in terms of access to credit: households without loans, households that borrowed from an MFI, households that borrowed from banks and households that have borrowed from both banks and microfinance. We exclude the later.[4] We are left with a sample of 348 households. As explained later, we also exclude households with bank loans in the main part of our empirical analysis when we evaluate the

[3]The maps are satellite pictures that give a clear image of the border of the DR, the streets and the location of dwellings. Each dwelling is marked by a dot. The images are of high quality, but they do not allow assessing the quality, age and status of the buildings.

[4]Only 12 households received loans both from microfinance and from the banking sector.

impact of improved credit access by the poor on the labor market behavior of the unemployed. Table 1 presents descriptive statistics of some characteristics of interest for each household type: without loans, with microcredit loan, with bank loan, and the full sample. The table also reports the results from a difference in means test between the households with no loan and those with access to some kind of lending, either through an MFI or through a bank.

The distribution of types is the same in urban and rural areas, indicating that there are no ex-post differences in credit access across the two strata. Looking at household size, we find that the households borrowing from either an MFI or a bank are on average of larger size than the households with no loan. Among MFI clients, the difference in size is particularly reflected in the number of children bellow working age in the household, which is significantly larger. Another important indicator to understand the targeting by the MFI concerns the fraction of households in which the head is a woman. The MFIs are often portrayed as targeting the women and, hence, we may expect households headed by a woman to be more frequent among the MFI clients. Comparing the MFI households to the households without loans, we find that among the former 59% are headed by a woman while this happens in only 50% of the households without loans. But, maybe surprisingly, the difference is not statistically significant. However, looking at the households that borrowed from a conventional bank, we find that only 33% of these households have a woman as head. Thus, it is apparent that for households headed by a woman, the MFI offer significantly more viable access to lending than the conventional banks. This finding confirms to some extent the traditional notion of the MFI targeting women.

An important variable is business ownership. The MFI in both the urban and rural areas often lend money to finance some form of household business, either formal or informal. One way to measure household entrepreneurship is to look at the fraction of households with at least one member self-employed. We find that 57% of the households borrowing from an MFI have at least one member self-employed. This is overwhelmingly more than among the households borrowing from banks and creditless at 28% and 31%, respectively. Turning to the number of unemployed individuals per household, we find that this number is 1.05 on average and there are no significant differences among the three groups of households. Households without loans have on average 1.69 sources of income, while the value is 1.80 for households with microfinance loans and 2.21 for households with bank loans. Households are also similar across types in terms of schooling achievement by the head and the spouse, with average schooling around 5 years. The standard errors are small, indicating very little dispersion. Thus, it is fair to say that the stylized representation of the household in Section 2, as a match between an entrepreneur and an unemployed worker, is not far from the typical household in our sample. It is unusual for households to have more than a single member unemployed and the typical household has one or two sources of income.

Table 2: Individual level characteristics of unemployed individuals

	Household access to lending					
	1: no loan		2: MFI loan		3: full sample	
# of households	264		84		348	
Female	0.64	(0.03)	0.61	(0.05)	0.64	(0.03)
Age	32.69	(0.76)	30.99	(1.40)	32.28	(0.67)
Schooling (years)	6.73	(0.26)	6.88	(0.45)	6.77	(0.22)
Owns mobile phone	0.63	(0.03)	0.57	(0.05)	0.62	(0.03)
Owns bank account	0.31	(0.03)	0.32	(0.05)	0.31	(0.03)
Is looking for a job (dummy)	0.52	(0.03)	0.45	(0.05)	0.50	(0.03)
Labor search intensity	0.87	(0.06)	0.70	(0.09)	0.83	(0.05)
# of initiatives to search for job	0.57	(0.04)	0.57	(0.08)	0.57	(0.04)
Unemployment duration: 1 — 6 months	0.17	(0.02)	0.13	(0.04)	0.16	(0.02)
Unemployment duration: 7 — 12 months	0.13	(0.02)	0.04**	(0.02)	0.11	(0.02)
Unemployment duration: 1 to 4 y	0.33	(0.03)	0.31	(0.05)	0.33	(0.03)
Unemployment duration: more than 4 y	0.27	(0.03)	0.41**	(0.05)	0.30	(0.02)

Standard errors in parentheses, *p<0.10, ** p<0.05, *** p<0.01.

The incidence of poverty is pervasive in our sample, in particular among households without any loan and households with microfinance loans. This is confirmed by the poverty head count, showing 28% of households with bank loans below the poverty line and head count rising to 57% and 52% among MFI borrowers and creditless households, respectively.[5]

Since we are interested on individual labor market outcomes of the unemployed, Table 2 reports some descriptive variables of interest at the individual level for the unemployed members of the household aged between 16 and 65, distinguishing by access to lending by the individual's household. It is interesting to notice that unemployed individuals from creditless households are similar to unemployed individuals from MFI households in almost all characteristics and especially job search variables such as whether or not they are looking for a job (dummy), the intensity of their job search and the number of initiatives taken to look for a job[6].

[5]We update the 2007 national poverty line (World Bank, 2007) by taking into account the inflation over the period 2007-2013. We attain an income value of 55,319 CVE per capita per year which is roughly equivalent to 2 US$ per capita per day in PPP. Households are considered poor if their income per capita per day is lower than 2 US$.

[6]Labor search intensity is an ordinal variable taking a value of 0 if the individual did not take any initiatives to find job, 1 if the individual searched a job on the internet or through families or friends and 2 if she sent open application, responded to job adds or participated in competitions. Number of initiatives to search for labor is an ordinal variable taking the value of 0, 1, 2 or 3 based on the number of different initiatives taken to find a job.

Another interesting feature of the data is that there seems to be a significantly higher share of long-term unemployment (more than 4 years) among individuals from households receiving micro loans.

4 Estimation Strategy and Identification Assumptions

We now introduce the econometric model used to asses the effects of improved access to credit on job search. The main purpose of the analysis is to test the Proposition 1 and, in particular, the prediction in equation (18). Of course, a simple evaluation based on differences in means is subject to multiple sources of bias. First borrowers can self-select into microfinance. They choose voluntarily whether to participate or not and this decision is correlated with various characteristics such as schooling, entrepreneurial spirit, ability, etc. In addition, biases can occur due to endogeneity of treatment: the MFI can select or exclude potential clients based on their resources, skills, ability, etc. A third concern is non-random program placement: the MFI may voluntarily choose to focus on a particular target group by locating their activities in given geographical areas. However, we do not consider this last concern as being problematic in our setting because it was clear from our data collection that the entire island of Santiago is covered by microfinance thanks to the large number of institutions and the easy mobility of their credit officers.

To correct for potential selection bias and appropriately estimate average treatment effects, we start from Rosenbaum and Rubin (1985)'s seminal paper, showing that, under the assumption of conditional independence, adjusting solely for differences between treated and control units in the propensity score removes all biases associated with differences in covariates. We define the propensity score as the conditional probability of receiving an MFI loan

$$\text{Propensity Score: } p(X) = p(T = 1 \mid X). \tag{19}$$

Conditional independence requires that conditional on the observable covariates, receiving treatment is independent of potential outcomes with and without treatment (Dehejia and Wahba, 2002; Imbens, 2004). This implies not only that the participation in the program is based entirely on observed characteristics, but also that average differences in outcomes between treated and control units with the same value of observed characteristics are attributable to the treatment.

$$\text{Conditional Independence Assumption: } Y_1, Y_0 \perp\!\!\!\perp T \mid X. \tag{20}$$

Hirano et al. (2003) extend Rosenbaum and Rubin (1985)'s result and show that weighting observations by the inverse of the estimated propensity score leads to an efficient estimate of the average treatment effect. The idea is to use the propensity scores as weights to obtain a balanced sample of treated and untreated individuals. The weights ensure that the covariates are uncorrelated with the treatment and, hence, the weighted estimator is consistent. We estimate the following equation

$$Y_i = \beta_0 + \beta_1 X_i + \delta_0 T_i + \delta_1 T_i \alpha_i + \epsilon_i, \tag{21}$$

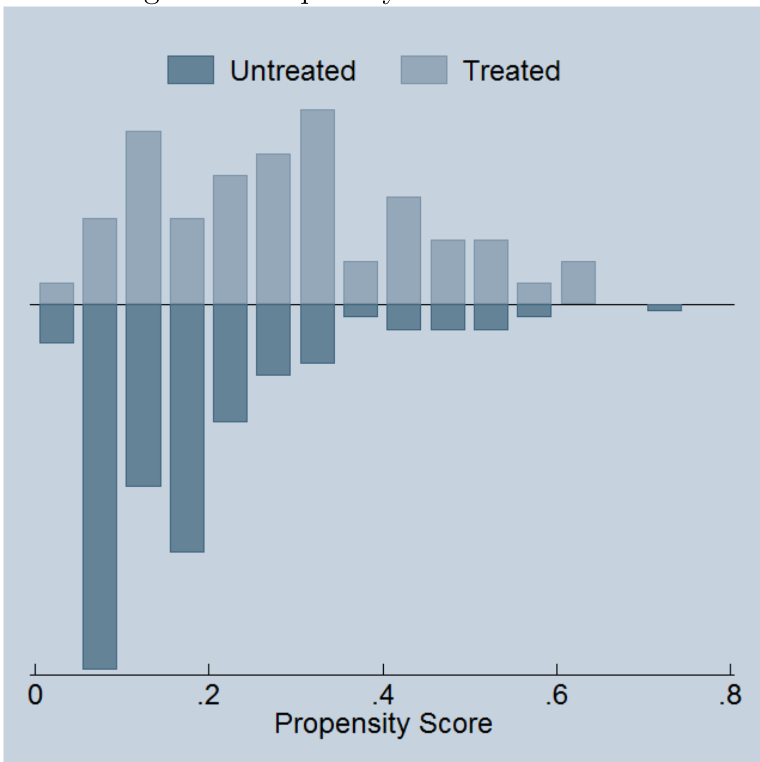
where T_i denotes the treatment and α_i is a proxy for the individual's bargaining power within the household. The control variables are in X_i and also include the bargaining power α_i. The weights are equal to unity for treated units and to $\widehat{p}(X)/(1-\widehat{p}(X))$ for controls where $\widehat{p}(X)$ is a consistent estimator of $p(X)$. To ensure that the weights add up to one, we normalize them to unity. This method is particularly useful to combine matching type estimators with other methods such as for example regressions with added covariates and fixed effects which enable researchers to evaluate the impact of the treatment but also of other covariates and their interactions.

5 Microfinance and Labor Search: Empirical Findings

We now turn to the empirical analysis to confront the theoretical predictions of our model with the data. The first step is to estimate a model for the probability of receiving a microfinance loan and hence estimate the propensity scores. We estimate a Multinomial Probit model with characteristics at the household level and we allow for three possible household status: receiving a loan from an MFI, receiving a loan from a bank and not receiving any loan (Caliendo and Kopeinig (2008), as discussed by Imbens (2000) and Lechner (2001)). Hence, we are effectively estimating a model of household access to credit. While being computationally heavier, the Multinomial Probit model is based on weaker assumptions (than for example the Multinomial Logit). Particularly, it does not rely on the independence of irrelevant alternatives assumption which allows for the correlation of household access to each available category. As explained in the previous section, the identification of the causal impact of the treatment (receiving a microfinance loan) is based on the assumption that allocation of the treatment is purely random among households having the same estimated probability or receiving a loan (propensity score), conditional on the pre-treatment characteristics. Hence, the participation equation should include variables that control for participation and outcomes of interest but that are not affected by the treatment.

The results of the first stage estimation are shown in Table 3. The participation equation is not a determinants model and what we are interested in is the correlation of X with T, rather than causality. Nonetheless we can see that household

Figure 1: Propensity Score Distribution



size and high education of the household head are important determinants of household access to lending by banks while house ownership decreases the probability of getting a microcredit, as does the fact that the head can read or write. Interestingly and perhaps somewhat surprisingly, the fact that the parent of the head was self-employed is associated with an increased probability of borrowing from a bank but not from a MFI.

The propensity score estimation enables us to predict the probability of getting access to microcredit at the household level. Figure 1 gives the kernel density of the estimated propensity scores for treated and non-treated households. As can be seen, there is substantial overlap in the distribution of the propensity scores of both treated and non-treated households.

As a second step, we estimate equation 21 at the individual level weighting observations of individuals in untreated households with the normalized odds of the estimated propensity scores. Our three dependent variables capturing labor search effort are (i) a dummy variable defined as taking a value of 1 if the unemployed individual took initiatives to find a job and 0 otherwise, (ii) an ordered variable capturing the intensity of labor search and (iii) an ordered variable capturing the number of initiatives taken to search for a job. To make sure we properly identify the impact of having access to microcredit on labor market outcomes, we further restrict our regression sample in the following ways. First, we exclude individuals who are members of households with access to bank loans. Second, we only consider households with micro loans received after 2009. Third, we enforce the common support condition which is an important assumption requiring sufficient overlap and balancing in the covariate distribution between treated and untreated individuals. This leads us to exclude treated individuals whose probability of participating is higher than the maximum probability of untreated individuals and untreated individuals whose probability of participating is lower than the minimum probability of treated individuals, i.e. we keep observations with propensity scores such that $0.038 \leq \widehat{p}(x) \leq 0.703$.

We begin with the analysis of the impact of having access to credit on the probability of job search (table 4). First, we see that it is important to control for self-selection using inverse probability weighting. The coefficient of treatment (MFI) becomes negative and significant when we do (column 2), compared to when we do not (column 1). The impact of having access to microcredit on job search seems to be negative (column 2).

We evaluate Proposition 1 and, in particular, equation (18) predicting that the search intensity of an unemployed member of a household with a loan compared to that of an unemployed in a household with no loan increases in the bargaining power α. As the bargaining power is not directly observable, we proxy it by variables correlated with individuals' bargaining power inside the household (columns 3—7), which we interact with the treatment variable 'MFI'. Interaction coefficients are significant and of the expected sign. Being a female as well as being a member of larger household, which are both associated with smaller bargaining power, have a negative impact on the search intensity of individuals who are part of a microcredit household. The effect of schooling, of having an educated parent and of the unemployed individual being the household head which are associated with a higher bargaining power also have the expected sign. Especially, having an educated parent or being the household head seems to compensate the negative impact of microcredit on individuals' job search intensity and make individuals increase their search intensity.

Table 3: Propensity score estimated using a multinomial probit model

	MFI Loan (1)		Bank Loan (2)	
# of hh members	0.103	(0.081)	0.267***	(0.087)
Head owns house	−0.613**	(0.307)	0.636	(0.421)
# of children 15 or younger	0.080	(0.131)	-0.227	(0.142)
Head has family abroad	0.718**	(0.317)	0.329	(0.309)
# of times per week reads journal	0.215	(0.291)	0.233	(0.274)
Head - read and write	0.062	(0.581)	0.575	(0.519)
Head - primary school	0.081	(0.672)	0.657	(0.630)
Head - high-school	−0.155	(0.818)	0.694	(0.746)
Head - college	0.353	(1.068)	2.485***	(0.868)
Parent of head was self-employed	0.416	(0.325)	0.656*	(0.362)
Head has a partner	−0.073	(0.310)	0.862**	(0.353)
Head is separated	0.273	(0.795)	−10.715***	(0.704)
Head is widower	−0.150	(0.503)	0.960	(0.626)
Head can read or write	−1.154*	(0.603)	−0.753	(0.499)
Head is from Santiago	0.349	(0.332)	0.577	(0.395)
Head is foreigner	0.660	(0.906)	−11.086***	(0.958)
head is woman	−0.285	(0.316)	−0.562*	(0.334)
Age of head	0.041	(0.056)	0.035	(0.059)
Age of head squared	−0.001	(0.001)	−0.001	(0.001)
Constant	−2.947**	(1.501)	−4.870***	(1.621)
Log pseudo likelihood				−211.706
Wald Chi2				5485.790
Prob > Chi2				0.000
Neighborhood fixed effects			yes	
Observations			317	

Robust standard errors in parentheses, *p<0.10, ** p<0.05, *** p<0.01.

Table 4: Estimated impact of access to microcredit on labor search (dummy)

	(1) Probit	(2) Probit	(3) Probit	(4) Probit	(5) Probit	(6) Probit	(7) Probit	(8) Probit
MFI	0.0257	-0.932**	0.830	-0.279	-2.097***	-2.868***	-0.905**	-1.024**
	(0.308)	(0.446)	(0.806)	(0.486)	(0.730)	(0.613)	(0.438)	(0.416)
MFI*HHSize			-0.268**					
			(0.106)					
MFI*Female				-1.002*				
				(0.583)				
MFI*Education					0.179**			
					(0.0703)			
MFI*ParentEducation dummy						2.906***		
						(0.668)		
MFI*Head							2.559***	
							(0.959)	
MFI*Bargaining Power PC								0.981***
								(0.355)
Hh size	0.155**	0.183**	0.319***	0.170*	0.167**	0.165*	0.146*	0.133
	(0.0655)	(0.0899)	(0.109)	(0.0894)	(0.0840)	(0.0847)	(0.0838)	(0.0866)
Female	-0.706***	-0.480	-0.298	-0.106	-0.566*	-0.513	-0.445	-0.476
	(0.216)	(0.336)	(0.358)	(0.355)	(0.334)	(0.321)	(0.332)	(0.328)
Number of years of schooling	-0.00190	0.0535	0.0458	0.0635	-0.0347	0.0633	0.0346	0.00668
	(0.0310)	(0.0461)	(0.0462)	(0.0454)	(0.0513)	(0.0454)	(0.0472)	(0.0480)
Parent Educated - dummy	-0.0353	-0.293	-0.470	-0.320	-0.250	-1.621***	-0.307	-0.586*
	(0.218)	(0.300)	(0.302)	(0.302)	(0.301)	(0.394)	(0.300)	(0.313)
Hh head dummy	-0.0545	0.935**	1.162***	0.824*	0.722	0.642	0.526	0.755*
	(0.314)	(0.452)	(0.442)	(0.443)	(0.483)	(0.441)	(0.518)	(0.450)
Unemployed duration: 7 - 12 months	0.868***	0.814	0.670	0.837*	1.070**	0.986*	0.784	1.128**
	(0.327)	(0.550)	(0.516)	(0.505)	(0.481)	(0.508)	(0.515)	(0.502)
Unemployed duration: 1 to 4 y	0.612***	0.516	0.415	0.562*	0.470	0.691**	0.438	0.619*
	(0.227)	(0.314)	(0.294)	(0.290)	(0.304)	(0.335)	(0.319)	(0.329)
Unemployed duration: more than 4 y	-0.645**	-0.317	-0.388	-0.330	-0.398	-0.324	-0.471	-0.290
	(0.262)	(0.355)	(0.339)	(0.349)	(0.359)	(0.351)	(0.359)	(0.369)
Other household level controls	yes	yes	yes	yes	yes	yes	yes	yes
Other individual level controls	yes	yes	yes	yes	yes	yes	yes	yes
Neighborhood FE	yes	yes	yes	yes	yes	yes	yes	yes
Inverse probability weighting	no	yes	yes	yes	yes	yes	yes	yes
Observations	262	262	262	262	262	262	262	262
Pseudo R-squared	0.306	0.584	0.598	0.591	0.602	0.642	0.598	0.607

Robust standard errors in parentheses, *p<0.10, ** p<0.05, *** p<0.01.

Since these variables capture different underlying features of bargaining power and hence income share, we also perform a principal component analysis (PCA), a method developed to aggregate information scattered in many numeric measures (Pearson (1901) and Hotelling (1933)).[7] Because for PCA to be valid, variables included should have a multivariate normal distribution or at least be continuous, and because we want to include a combination of dichotomous and continuous variables (female, parent education, household size, education and age), we perform a polychoric correlation analysis (Kolenikov and Angeles (2004)). Pairwise correlations between each variables are estimated based on the nature of the variable: Pearson moment correlation if the two variables are continuous, polychoric correlation if the two variables are ordinal and polyserial correlation if one variable is ordinal and the other continuous. We can then run a principal component analysis on the resulting correlation matrix and interpret the first principal component as the index of bargaining power. Results are presented in column (8) and also confirm our theoretical prediction. Unemployed individuals members of households having access to microcredit will have a higher job search intensity, the higher their bargaining power.

We then replicate the analysis with our second dependent variable of interest, the labor search intensity.[8] It can be seen from table 5 that results are quantitatively and qualitatively similar to the results of table 4 which were just described.

Finally, the estimation results with our third dependent variable of interest, the number of labor search initiatives are presented in table 6. Precision and significance of the estimates decrease quite a lot. However, the coefficient of the interaction terms 'MFI * Parent Education', 'MFI * Head' and 'MFI * Bargaining power' remain significant and of the expected sign.

[7] See Filmer and Pritchett (2001) for one of the earliest and most influential paper in development economics and population studies where the authors construct socio-economic indices using PCA.

[8] The only difference is that we use an ordered probit model which is a generalization of the probit model for an ordinal dependent variable that has more than two outcomes.

Table 5: Estimated impact of access to microcredit on labor search intensity

	(1) Oprobit	(2) Oprobit	(3) Oprobit	(4) Oprobit	(5) Oprobit	(6) Oprobit	(7) Oprobit	(8) Oprobit
MFI	-0.0603	-0.780*	1.528*	-0.139	-2.167***	-2.787***	-0.750*	-1.028***
	(0.265)	(0.400)	(0.837)	(0.434)	(0.667)	(0.575)	(0.383)	(0.395)
MFI*HHSize			-0.349***					
			(0.116)					
MFI*Female				-1.140**				
				(0.569)				
MFI*Education					0.199***			
					(0.0652)			
MFI*Parent Education dummy						3.048***		
						(0.640)		
MFI*Head							1.397*	
							(0.836)	
MFI*Bargaining Power PC								1.201***
								(0.376)
Hh size	0.0124	-0.117	0.0161	-0.109	-0.104	-0.0944	-0.128	-0.124
	(0.0545)	(0.0892)	(0.0980)	(0.0890)	(0.0831)	(0.0818)	(0.0865)	(0.0845)
Female	-0.727***	-0.547*	-0.268	-0.192	-0.631**	-0.380	-0.506*	-0.507*
	(0.195)	(0.296)	(0.314)	(0.336)	(0.299)	(0.290)	(0.304)	(0.286)
Number of years of schooling	0.0239	0.0838**	0.0702*	0.0938**	-0.00367	0.0802**	0.0663	0.0321
	(0.0273)	(0.0407)	(0.0403)	(0.0399)	(0.0455)	(0.0394)	(0.0408)	(0.0411)
Parent Educated - dummy	0.113	0.0887	-0.322	-0.0318	0.0869	-1.245***	0.138	-0.351
	(0.191)	(0.298)	(0.307)	(0.303)	(0.291)	(0.360)	(0.297)	(0.309)
Hh head dummy	-0.0324	0.729*	1.200***	0.591	0.261	0.609	0.239	0.530
	(0.290)	(0.409)	(0.436)	(0.393)	(0.437)	(0.377)	(0.536)	(0.388)
Unemployed duration: 7 - 12 months	0.601**	-0.0528	-0.0248	-0.0808	0.521	0.0992	0.0429	0.387
	(0.276)	(0.410)	(0.416)	(0.391)	(0.421)	(0.388)	(0.385)	(0.412)
Unemployed duration: 1 to 4 y	0.414**	0.590*	0.676**	0.652**	0.591*	0.861**	0.540	0.743**
	(0.210)	(0.336)	(0.339)	(0.321)	(0.334)	(0.342)	(0.341)	(0.343)
Unemployed duration: more than 4 y	-0.562**	-0.188	-0.0348	-0.193	-0.236	-0.185	-0.329	-0.135
	(0.253)	(0.371)	(0.394)	(0.370)	(0.378)	(0.359)	(0.373)	(0.375)
Other household level controls	yes	yes	yes	yes	yes	yes	yes	yes
Other individual level controls	yes	yes	yes	yes	yes	yes	yes	yes
Neighborhood FE	yes	yes	yes	yes	yes	yes	yes	yes
Inverse probability weighting	no	yes	yes	yes	yes	yes	yes	yes
Observations	262	262	262	262	262	262	262	262
Pseudo R-squared	0.206	0.419	0.441	0.429	0.443	0.482	0.426	0.453

Robust standard errors in parentheses, *p<0.10, ** p<0.05, *** p<0.01.

Table 6: Estimated impact of access to microcredit on the number of labor search initiatives

	(1) Oprobit	(2) Oprobit	(3) Oprobit	(4) Oprobit	(5) Oprobit	(6) Oprobit	(7) Oprobit	(8) Oprobit
MFI	0.171	-0.379	0.500	0.134	-0.976	-2.042***	-0.332	-0.597
	(0.273)	(0.360)	(0.769)	(0.440)	(0.761)	(0.513)	(0.342)	(0.376)
MFI*HHSize			-0.130					
			(0.0967)					
MFI*Female				-0.897				
				(0.613)				
MFI*Education					0.0807			
					(0.0781)			
MFI*Parent Education dummy						2.408***		
						(0.604)		
MFI*Head							1.698**	
							(0.698)	
MFI*Bargaining Power PC								0.697**
								(0.353)
Hh size	0.0533	-0.0334	0.0224	-0.0227	-0.0310	-0.0157	-0.0578	-0.0392
	(0.0546)	(0.0680)	(0.0816)	(0.0669)	(0.0664)	(0.0649)	(0.0690)	(0.0664)
Female	-0.598***	-0.297	-0.175	0.00867	-0.348	-0.0959	-0.238	-0.279
	(0.195)	(0.300)	(0.292)	(0.308)	(0.310)	(0.299)	(0.308)	(0.305)
Number of years of schooling	0.0227	0.0527	0.0467	0.0608	0.0164	0.0512	0.0362	0.0210
	(0.0248)	(0.0407)	(0.0418)	(0.0385)	(0.0459)	(0.0401)	(0.0412)	(0.0426)
Parent Educated - dummy	0.00644	0.0542	-0.0823	-0.0819	0.0528	-1.041***	0.0531	-0.206
	(0.178)	(0.234)	(0.234)	(0.259)	(0.235)	(0.300)	(0.229)	(0.255)
Hh head dummy	0.0249	0.986***	1.147***	0.902**	0.801*	0.844**	0.444	0.856**
	(0.283)	(0.381)	(0.404)	(0.365)	(0.432)	(0.344)	(0.475)	(0.366)
Unemployed duration: 7 - 12 months	0.506*	0.241	0.221	0.322	0.477	0.447	0.315	0.569
	(0.273)	(0.466)	(0.477)	(0.468)	(0.522)	(0.504)	(0.464)	(0.511)
Unemployed duration: 1 to 4 y	0.471**	0.203	0.200	0.298	0.204	0.417	0.157	0.307
	(0.200)	(0.370)	(0.381)	(0.372)	(0.377)	(0.396)	(0.378)	(0.394)
Unemployed duration: more than 4 y	-0.494**	-0.0377	-0.0216	-0.0400	-0.0471	-0.0357	-0.201	0.0169
	(0.244)	(0.408)	(0.417)	(0.412)	(0.412)	(0.409)	(0.414)	(0.429)
Other household level controls	yes	yes	yes	yes	yes	yes	yes	yes
Other individual level controls	yes	yes	yes	yes	yes	yes	yes	yes
Neighborhood FE	yes	yes	yes	yes	yes	yes	yes	yes
Inverse probability weighting	no	yes	yes	yes	yes	yes	yes	yes
Observations	262	262	262	262	262	262	262	262
Pseudo R-squared	0.207	0.381	0.386	0.389	0.386	0.434	0.393	0.396

Robust standard errors in parentheses, *p<0.10, ** p<0.05, *** p<0.01.

6 Conclusion

To be added.

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