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

Paolo Casini[†], Olivia Riera[‡], Paulo Santos Monteiro[§]

December 17, 2014

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.

JEL classification codes: D13; D14; J20; O11; O12.
Keywords: Microfinance; Bargaining Power; Collective Household; Job Search.

*Thanks to seminar participants at KU Leuven, University of York, St Andrew University, the IDEAS 2014 Summer School in Development Economics in Garda and the PEJ 2014 annual meeting in Braga for helpful comments. We also benefited from excellent research assistance from Sofía Barbosa, Natália Barros, Vasco Miranda, Jassira Monteiro, Edmilson Tavares, Ingla Tavares, Zuleica Veiga and Arsénia Veiga.

[†]KU Leuven
[‡]KU Leuven
[§]University of York

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. We find empirical support for the predictions of the model using a household survey conducted in Cape Verde.

Targeting benefits to a particular household member (for example to women instead of men) has been shown to have important effects on the ultimate use of the corresponding resources (Cherchye et al., 2012). 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 should 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 both 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, we show that the impact of improved access to credit on search intensity by the unemployed is affected by two competing effects. Having access to finance may raise search intensity, as it increases the return to the household's net-worth and, by finding a job, the unemployed worker raises the household's net-worth. But at the same time, unemployed individuals in households with better access to finance enjoy 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 is high the positive net-worth effect is relatively stronger and, hence, improved access to credit is more likely to raise search effort by the unemployed.

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. We make use of unique detailed individual data on labor search behavior of unemployed individuals which allows us to test empirically the theoretical predictions. We find robust support for the model's 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. The 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 individual bargaining power variables such as gender, schooling achievement, household size and the individual role in the 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. More recently, Ashraf (2009), by looking at couples' financial decisions in the Philipines, suggests that above the gender dimension, it is control of financial decision that matters most. In a recent experiment offering cheaper and more accessible bank accounts in Kenya, Schaner (2013) further supports this idea, showing that responses to the program varied according to whether both men and women were above or below the median bargaining power and not according to gender solely.

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 to cash-on-hand using sharp discontinuities in eligibility for severance pay and extended unemployment insurance in Austria. Their findings provide important implications for the efficiency of social insurance programs.

In our context, the microfinance institutions play an important role in relaxing credit constraints faced by poor households. Relaxing credit constraints may change the investment opportunities available to households but, at the same time, may affect labor market outcomes depending on the distribution of decision power within the household. For instance, in a recent paper Ngo and Wahhaj (2012) develop a model of household production, bargaining and credit and show that if there is scope to invest loans in profitable joint activities women are most likely to benefit from improved access to credit. Callen et al. (2014) look at the effects of improved access to financial services on the incentives to provide wage work. They conduct a natural experiment in Sri Lanka where improved access to saving products is randomly assigned. They find that households work more, and work more on the wage market when savings options improve. They propose an explanation for their findings based on the fact that an increase in the return to savings encourages more wage work. This effect is not dissimilar to the mechanism we propose in our paper.

In the context of testing the effects of microfinance using models of collective household choice, looking at the labor market behavior and, in particular, our focus on the search intensity of the unemployed, is attractive because leisure is a private good. Pitt and Khandker (1998) and also Morduch (1998) find that participation in microcredit programs has heterogenous effects on labor supply, depending on the borrower's gender.

Likewise, our analysis provides important insights on positive and normative issues concerning the design of microfinance programs and, in particular, the targeting of microcredit. The improved access to credit by the poor that is made possible by microfinance can affect labor market behavior in a positive way. But this complementarity is not unconditional and depends crucially on how the loans are targeted among heterogeneous households. Relaxing credit constraints to poor households may have complementarities with improved labor market outcomes but may also discourage the supply of wage labor. Which effect prevails, depends on the targeting of loans. This result resonates with findings by Ahlin et al. (2011) who find evidence of a rivalrous relationship between microfinance and other modes of development and, in particular, workforce participation.

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. We propose a model of job search and household collective choice, in an environment with search frictions and financial constraints. There are two periods, date 0 and date 1. A household consists of a match between an entrepreneur and a wage laborer. The latter starts date 0 unemployed. As in Card et al. (2007), 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 who are able to borrow from a microfinance institution (MFI) and those without access to credit. The former are able to finance an indivisible 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.

2.1 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 is implemented by assuming that the household's problem is represented by an objective function which is a weighted sum of the private utility function of each household member; the weights may be interpreted as the bargaining power of each individual in the household as done, for example, in Anderson and Baland (2002), Blundell et al. (2005) and Cherchye et al. (2012). 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 type is pre-determined, known at date 0. The timing is as follows: at the start of date 0, households choose the search effort of the unemployed worker, $S(t)$, and the household's contingent consumption allocations. At the end of date 0, those unemployed workers who successfully search and become employed receive their wage W, and the households with access to credit borrow from the MFI and invest the loan and all their net-worth in the high return technology. The crucial feature of our model is the assumption that the unemployed individuals who succeed in finding a job can contribute with their wage to the investment, hence reducing the size of the loan. At date 1, households receive the returns from the entrepreneurial activity, repay their loan and enjoy consumption.

The contingent consumption allocation is defined as:

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

where $\mathbb{C}_e(t)$ is the allocation in the event that the job search is successful while

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

$\mathbb{C}_n(t)$ is the allocation in the event that the wage laborer stays unemployed; $\widehat{C}$ is the consumption of the entrepreneur and C that of the wage laborer.

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 two key simplifying assumptions: first, we assume there is a single wage rate; and second we assume that utility is separable in consumption and search effort and is represented by the utility function:

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

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. The function $v(\bullet)$, is a quadratic function capturing the disutility from search, and is decreasing and concave in the domain $[0,1]$. The function $u(\bullet)$ is assumed to be increasing, concave and homothetic, and to satisfy the condition $u'''(\bullet) \geq 0$.[2]

Let $R \geq 1$ be the gross return to investment, $r \in [0,1]$ be the market interest rate and A the household's financial assets at the start of date 0. In the second period, when consumption takes place, the household total resources, $Y(t)$, are given by:

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

The problem solved by the household is represented by the program:

$$\begin{aligned} &\max_{S, \mathbb{C}_e, \mathbb{C}_n} \; \mathbf{J}(S, \mathbb{C}_e, \mathbb{C}_n; t), \\ &\text{subject to } \; \widehat{C}_i(t) + C_i(t) \leq Y_i(t), \quad i = e, n. \end{aligned} \tag{4}$$

[2] The convex marginal utility case, i.e. $u'''(\bullet) \geq 0$, plays an important role in the theory of precautionary saving (Kimball, 1990) and is a feature of the popular CRRA class of utility functions.

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

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

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

2.2 Finance and Search Intensity

We first show that the impact that having access to micro-loans has on search intensity by the unemployed is ambiguous, as there are two competing effects. 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

$$\begin{aligned} C_{n}\left(t\right)&=\left(1+f\left(\alpha\right)\right)^{-1}Y_{n}\left(t\right) \quad \text{and}\\ C_{e}\left(t\right)&=\left(1+f\left(\alpha\right)\right)^{-1}Y_{e}\left(t\right). \end{aligned} \quad (10)$$

Define the function

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

such that the optimality condition for the choice of search intensity (9), can be expressed as

$$-\alpha v'\left(S\left(t\right)\right)=\Delta\left(C_{e},C_{n};t\right). \quad (12)$$

To identify the two competing effects of finance on job search intensity, take the first-order Taylor expansion of $\Delta(C_e, C_n; t)$ around

$$\left\{C_e^{\bullet}(t), C_n^{\bullet}(t)\right\} = \left\{(1+f(\alpha))^{-1} Y_n(t), (1+f(\alpha))^{-1} Y_n(t)\right\} \tag{13}$$

and impose the budget constraint (10). This yields

$$\widetilde{\Delta}(\alpha; t) = \begin{cases} \hat{u}'\left((1+f(\alpha))^{-1} Y_n(1)\right)\left[(1+f(\alpha))^{-1}(1+r) W\right], & t=1 \\ \\ \hat{u}'\left((1+f(\alpha))^{-1} Y_n(0)\right)\left[(1+f(\alpha))^{-1} W\right], & t=0 \end{cases} \tag{14}$$

with $\widetilde{\Delta}(\alpha; t)$ that denotes the Taylor expansion of $\Delta(C_e, C_n; t)$ around (13).[3]

Ignoring higher order terms,[4] the optimality condition for the choice of search intensity can be expressed as

$$-\alpha v'(S(t)) = \widetilde{\Delta}(\alpha; t). \tag{12$'$}$$

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

$$\frac{dS(t)}{dt} = -\frac{d\widetilde{\Delta}(\alpha; t)/dt}{\alpha v''(S(t))}, \tag{15}$$

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

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

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

$$\hat{u}'\left((1+f(\alpha))^{-1} Y_n(1)\right) < \hat{u}'\left((1+f(\alpha))^{-1} Y_n(0)\right), \tag{17}$$

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.

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

[3]See Appendix A for details.

[4]This is without loss of generality, since we want to show that the change in $S(t)$ conditional on treatment is ambiguously signed. For that, it suffices to show that the first order change in $\Delta(C_e, C_n, t)$ is ambiguous.

To see this first notice that, because $v''(\bullet)$ is a constant ($v(\bullet)$ is a quadratic function), we have from ($12'$) that

$$\frac{S(1)}{S(0)}=\frac{\widetilde{\Delta}(\alpha;1)}{\widetilde{\Delta}(\alpha;0)}=\frac{\hat{u}'\left((1+f(\alpha))^{-1}Y_n(1)\right)(1+r)}{\hat{u}'\left((1+f(\alpha))^{-1}Y_n(0)\right)}. \tag{18}$$

We are interested in the sign of the derivative

$$\begin{aligned}\frac{\partial\left({}^{S(1)}/_{S(0)}\right)}{\partial\alpha}&=\partial\left[\frac{\hat{u}'\left((1+f(\alpha))^{-1}Y_n(1)\right)}{\hat{u}'\left((1+f(\alpha))^{-1}Y_n(0)\right)}\right]\frac{(1+r)}{\partial\alpha}=\left[\frac{-f'(\alpha)(1+r)}{(1+f(\alpha))^2}\right]\\&\times\left[\frac{\hat{u}''(C_n(1))\,\hat{u}'(C_n(0))\,Y_n(1)-\hat{u}''(C_n(0))\,\hat{u}'(C_n(1))\,Y_n(0)}{\hat{u}'(C_n(0))^2}\right]>0.\end{aligned} \tag{19}$$

The derivative is positive since $f'(\alpha)<0$ and $C_n(0)<C_n(1)$, which implies that $u'(C_n(0))\geq u'(C_n(1))$ and $u''(C_n(0))\leq u''(C_n(1))$.[5]

The reason why the effect of improved access to credit on search is more positive (or less negative) for individuals with higher bargaining power is because the strength of the income effect is weaker if consumption is high. In turn, if the bargaining power of the unemployed worker is high his/her consumption will be relatively high, since he/she receives a higher fraction of the household resources. Thus, the income effect is weaker and the net-worth effect dominates.

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:*

$$\frac{\partial\left({}^{S(1)}/_{S(0)}\right)}{\partial\alpha}>0. \tag{20}$$

[5]This follows from $\hat{u}''(\bullet)<0$ and $\hat{u}'''(\bullet)\geq 0$.

The proposition suggests two observations. First, that the effect of treatment on job search is ambiguous and hence, invites further empirical investigation. Second, the model provides a clear testable prediction: as the bargaining power of the unemployed member increases, the effect of improved access to finance on search intensity should become more positive (or less negative). In the sequel, we test this prediction using the survey data that we have collected in Cape Verde.

3 Survey Design and Data

We use data from a household survey undertaken by the authors in the Isle of Santiago, Cape Verde, in 2013, as part of a broader project evaluating the impact of microfinance in the country. We begin by describing the survey design and sampling methods.

3.1 Survey Design and Sample

The original sample contains 600 households and is obtained using a stratified random sampling technique. In particular, we are interested in labor market outcomes and, since job and business opportunities differ considerably between urban and rural settings, the principal dimension of stratification is whether households live in an urban or rural area.

Thanks to detailed interviews to the main microfinance institutions that operate in the country, we identify the areas where microfinance clients are more likely to reside. In the capital city, Cidade da Praia, we chose 10 neighborhoods based on their relevance for microfinance.[6] We exclude the wealthier neighborhoods and those where the employment rate is well above the national average as reported in the 2010 National Census.

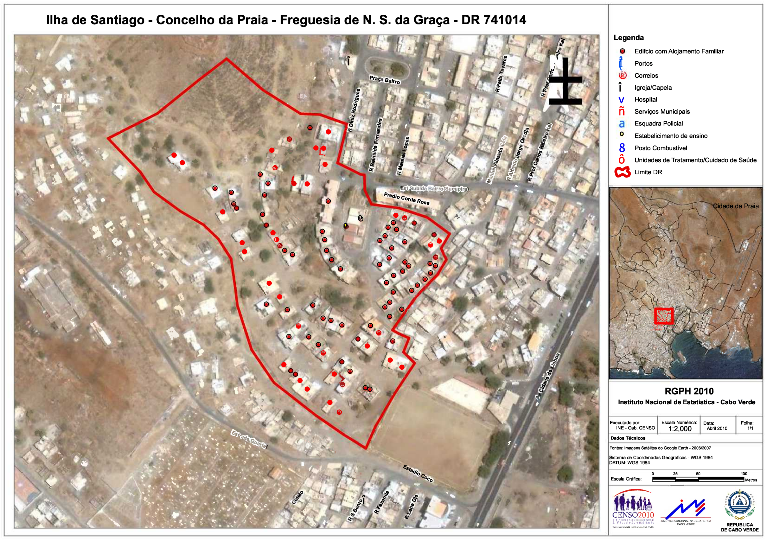
Our primary sampling unit in Cidade da Praia (urban stratum) are 20 randomly selected census districts (CD) that overlap the selected neighborhoods.[7] Each CD contains 180 dwellings (and so approximately 180 households). Concerning the stratum of rural households, we choose three areas characterized by high population density and a large number of MFI clients, and randomly selected 10 CD in each of these areas.[8] Finally, from each CD, both urban and rural, we randomly select 20 households using maps provided by the national statistics

[6]The neighborhoods are Fazenda, Achadinha, Várzea, Terra Branca, Safende, Achada Grande de Frente, Achada Grande de Trás, Ponta d'Água, São Felipe and Achada de Santo António.

[7]Census Districts are precisely delimited geographical areas, drawn for the 2010 National Census and covering the entire national territory.

[8]The selected areas are Assomada, Calheta de São Miguel and Pedra Badejo

Figure 1: Satellite picture of a census district (CD)



institute, like the one shown in Figure 1.[9] Moreover, the households refusing to be interviewed are very few and so are the households in which not a single member is present.[10] Given the CD design, this procedure guarantees that each household has approximately the same probability of being interviewed.

The survey elicits detailed information on demographic characteristics, income, consumption, assets and a complete recording of the financial services used by the household, related to both microfinance and other forms of financial services. In particular, we have information on all kinds of loan received by households (either from conventional commercial banks or from an MFI). Thus, we can distinguish 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 borrowed from both banks and an MFI. In addition, we have detailed information on the labor market participation of each member and, in particular, on the job search effort by the unemployed and on the length of their unemployment spell.

[9]The maps are satellite pictures that give a clear image of the border of the CD, 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. The enumerators were asked to abide by the following protocol: *'Interview only the households in the randomly selected dwellings marked on the maps; if a dwelling turns out to be abandoned, go to the nearest one. If the dwelling hosts more than one household, select the first door to the right'.* Reassuringly, there are very few abandoned dwellings, probably because of the rapid increase of the population in the isle of Santiago.

[10]This, is mainly due to the fact that many households still have a traditional structure and are formed by different cohabiting generations (often, grandparents, parents and sons), so that dwellings are rarely empty and there is always someone able to speak to visitors. Besides, it testifies to the friendliness of Cabo Verdeans.

Few restrictions are imposed on the original sample of surveyed households. First, since we are interested in the effects of improved access to credit on the search behavior of the unemployed, we drop households that have no members aged between 16 and 65 years old who are unemployed. Second, we exclude households that borrowed from both banks and an MFI.[11] We are left with a sample of 317 households. The 317 households correspond to 1,100 individuals. Among the 1,100 individuals, 620 are employed and 480 unemployed.[12]

We restrict the sample further in the second stage, when we evaluate the impact of improved credit access on the labor market behavior of the unemployed. First, we exclude households with commercial bank loans. Second, to comply with the common support assumption underlying Propensity Score Matching techniques we exclude households with extreme propensity scores (probability of receiving an MFI loan). Third, we exclude from the treated group the households who received their MFI loan earlier than 2010.[13] The sample in our main regression analysis includes 262 unemployed individuals, corresponding to 191 households. Individuals are defined as unemployed if they are between 16 and 65 and claim to be unemployed, either looking for a job or not actively engaged in search (rest unemployment).[14]

3.2 Preliminary Data Description

Table 1 describes the main characteristics of each household type, together with the results from a difference in means test between the households with no loan and those with access to finance, either through an MFI or through a bank.

The frequency 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 reflected in the number of children below working age which is significantly larger. An important indicator to understand the targeting by the MFI is the fraction of households in which the head is a woman. The MFI are often portrayed as targeting the women and, hence, we

[11] Only 12 households received loans from both an MFI and a bank.

[12] Specifically, as shown in Table 2, there are 315 unemployed individuals in households without loan, 86 unemployed individuals in households with MFI loans and 79 unemployed individuals in households with bank loans.

[13] This is to comply with the important assumption of our model that individuals know if their household has access to finance when they choose their search effort. Since the MFI typically have several repeated interactions with their clients, it is reasonable to assume that those who recently received loans and did not default have easier access to finance.

[14] This is the appropriate definition of unemployment as we are interested in the effects of improved access to credit on job search effort.

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	218		56		43		317	
Rural household (%)	30	(0.03)	29	(0.06)	26	(0.07)	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 (%)	51	(0.03)	59	(0.07)	33**	(0.07)	50	(0.03)
Age of head	49.33	(1.09)	48.46	(1.77)	52.58	(2.16)	49.62	(0.86)
Head's schooling (years)	4.68	(0.27)	4.14	(0.51)	5.58	(0.63)	4.71	(0.22)
Spouse's schooling (years)	4.78	(0.46)	5.15	(0.64)	4.79	(0.67)	4.84	(0.33)
Head is unemployed (%)	35	(0.03)	29	(0.06)	16***	(0.06)	31	(0.03)
Spouse is unemployed (%)	27	(0.03)	18	(0.05)	47**	(0.08)	28	(0.03)
# of members self-employed	0.30	(0.04)	0.57***	(0.09)	0.28	((0.09)	0.34	(0.03)
# of members unemployed	1.64	(0.06)	1.60	(0.10)	2**	(0.18)	1.68	(0.05)
# of income sources	1.69	(0.08)	1.80	(0.15)	2.21***	(0.21)	1.77	(0.07)
Total annual income p.c. (CVE)	86,700	(8,637)	74,304	(12,182)	129,169*	(22,146)	90,271	(7,032)
Poverty headcount ratio (%)	51	(0.03)	57	(0.07)	28***	(0.07)	49	(0.03)

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

may expect households headed by a woman to be more frequent among the MFI clients. We find that 59% of the MFI households are headed by a woman while this happens in 51% of the households without loans, but the difference is not statistically significant. However, looking at the households that borrowed from a conventional bank, we find that only 33% of them have a woman as head. Thus, 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 widely spread notion of the MFI targeting women. In terms of schooling achievement, households are similar across types, with average schooling around 5 years.

Another variable of interest is self-employment. MFI in both urban and rural areas typically give out loans to finance some form of business, either formal or informal. One way to measure 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 substantially more than among households borrowing from banks (28%) and households not borrowing (30%). Turning to the number of unemployed per household, we find an average of 1.68, with no significant differences among microfinance and no-loan groups. The average number of unemployed individuals is significantly higher for households borrowing from banks, as is the number of income sources.[15] Households without loans have on average 1.69 sources of

[15] Families with bank loans have higher income than families borrowing from the MFI. The higher unemployment rate among this group suggests that leisure is a normal good. This is consistent with our definition of unemployment, that includes rest unemployment.

Table 2: Individual level characteristics of unemployed

	Household type					
	1: no loan		2: MFI loan		3: full sample	
# of individuals	315		86		401	
Female (%)	64	(0.03)	61	(0.05)	63	(0.02)
Age	33	(0.73)	31	(1.40)	33	(0.65)
Schooling (years)	6.67	(0.24)	6.90	(0.46)	6.71	(0.21)
Owns mobile phone (%)	63	(0.03)	57	(0.05)	61	(0.03)
Owns bank account (%)	30	(0.03)	33	(0.05)	31	(0.03)
Is looking for a job (dummy) (%)	51	(0.03)	45	(0.05)	50	(0.03)
Job search intensity	0.86	(0.06)	0.71	(0.09)	0.83	(0.05)
# of initiatives to search for job	0.55	(0.04)	0.58	(0.08)	0.56	(0.04)
Unemployment duration: 1 — 6 months (%)	18	(0.02)	13	(0.04)	17	(0.02)
Unemployment duration: 7 — 12 months (%)	12	(0.02)	4**	(0.02)	10	(0.02)
Unemployment duration: 1 to 4 y (%)	32	(0.03)	33	(0.05)	32	(0.03)
Unemployment duration: more than 4 y (%)	26	(0.03)	40**	(0.05)	29	(0.02)

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

income, while the value is 1.80 for those with micro-loans. 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. On average, households have one or two members unemployed and one or two sources of income.

The incidence of poverty is pervasive in our sample, in particular among the households with no access to finance and with micro-loans, our core sample. This is confirmed by the poverty head-count, showing 28% of households with bank loans below the poverty line, with the share rising to 57% among MFI borrowers and 51% among households with no loans.[16]

Table 2 reports individual characteristics of interest of the unemployed individuals aged between 16 and 65 that are members of households in the treatment and in the control group (hence, after the exclusion of households borrowing from banks). It is interesting to notice that unemployed individuals from households with no loans are very similar to unemployed individuals from MFI households,

[16]Since no recent information in this respect is available, we updated 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$.

Table 3: Loan characteristics of treated households

	Descriptives
# of households	56
Number of loans per hh	1,7
Female clients (%)	83
Main use of the loan: business related (%)	82.5
Loan size (average) (CVE)	62,200
Loan size (median) (CVE)	50,000
Loan duration (months)	8
Default rate (%)	8
Difficulty to repay (%)	6

especially for job search measures.[17] Another interesting observation is that there is a significantly higher share of long-term unemployment (unemployment spells longuer than 4 years) among members of households borrowing from an MFI, but lower medium term unemployment.

Finally, some characteristics of the micro loans taken by the treated households are displayed in Table 3. First, it can be seen that women represent a high proportion of clients, at 83%. The microfinance loan was taken for business related purposes in 82.5% of the cases (to start a business, expand it, buy goods for petty trade or buy work equipment), which is consistent with the intrinsic objective of microfinance to promote entrepreneurship. Looking at the loan size, we see that the distribution is right skewed, the average amount lent being higher than the median.[18] Finally, looking at loan performance, only 8% of clients defaulted and 6% had difficulties in repaying the loan.[19]

[17]The job search measures constructed are the following three: *Is looking for a job*; *Labor search intensity*; and *Number of initiatives to search for work*. The first, *Is looking for a job*, is a discrete variable taking value 1 if the unemployed individual has taken any initiative to find a job in the previous four weeks and 0 otherwise; The second, *Labor search intensity* is an ordinal variable capturing the intensity of labor search. It takes value 0 if the individual did not take any initiatives to find job; 1 if the individual searched a job on the internet, asked help from friends, family or worker union, or registered in a job center; and 2 if she asked an employer for work, took part in a job selection process or responded to a job offer. The rational of this variable is to rank the amount of effort needed for the different types of initiatives in the context of Cape Verde. *Number of initiatives to search for work* is a cardinal variable taking the values 0, 1, 2 or 3 depending on the number of different initiatives taken to find a job.

[18]The median loan size is equal 588 $US. 1 US dollar is roughly equal to 85 Cape Verdean Escudo (CVE), the national currency.

[19]A loan is considered in default if it is still ongoing 3 months after the due date.

4 Estimation Strategy and Identification Assumptions

In this Section we introduce the econometric model used to assess the effects of improved access to credit on job search. The main purpose of the analysis is to test Proposition 1 and, in particular, the prediction in Equation (20). We seek to estimate the impact of household borrowing from an MFI on the job search effort by the unemployed household members: the Average Treatment Effect for the Treated (ATT).

Formally, $Y(1)$ is the outcome, job search effort, for an individual in a household borrowing from an MFI and $Y(0)$ the outcome for an individual in a household without microfinance access. Let t be the indicator of treatment, with $t = 1$ if the household has received a microfinance loan and $t = 0$ if it has not. We wish to evaluate the difference between the outcome of individuals in treated households and the counterfactual outcome of the same group of individuals had they not received the loan, given a vector X of observable characteristics

$$\text{ATT} = E\left[Y(1) \mid X, t = 1\right] - E\left[Y(0) \mid X, t = 1\right]. \tag{21}$$

The evaluation problem lies in the fact that, for each individual, only one of either $Y(1)$ or $Y(0)$ are observed. In particular, for individuals in households with $t = 1$, only $Y(1)$ is observed. We need a counterfactual based on the observable outcome of the non-treated households, built in such a way to be as close as possible to the theoretical outcome for individuals in treated household in the absence of treatment. The obvious candidate is to use the outcome of individuals in the non-treated households, $E\left[Y(0) \mid X, t = 0\right]$, as a counterfactual. However, an evaluation based on differences in means is subject to various sources of bias when treatment is not randomly assigned and is, instead, determined by multiple household characteristics such as schooling, entrepreneurial spirit and ability.

In their seminal paper, Rosenbaum and Rubin (1985) propose a method that corrects for potential selection and omitted variable bias in estimating ATT. They show that, under the assumption of conditional independence, adjusting for differences between treated and control units in the propensity score removes all biases associated with differences in the observed covariates in the treated and control groups. The propensity score is defined as the conditional probability of receiving an MFI loan:

$$p(X) = \text{Prob}\left(t = 1 \mid X\right), \tag{22}$$

where X are observed covariates, which are assumed to be pre-determined.[20]

[20] The conditional independence assumption, or unconfoundedness property, requires that, conditional on the observed covariates, receiving treatment (having an MFI loan) is independent of the potential outcomes (the search intensity) with and without the treatment, Y_1 and Y_0. This implies not only that 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 observed characteristics are attributable to the treatment, so that $t \perp Y(1), Y(0) \mid X$.

For each household j, the estimated propensity score $\widehat{p}(X_j)$ is estimated based on a range of observable pre-program household characteristics, collected in the vector X_j. The access to credit is modeled at the household level as we want to distinguish between the households who borrow from the MFI and those that do not. Thus, we include only household level covariates in the probability model.[21]

Hirano et al. (2003) extend Rosenbaum and Rubin (1985)'s result and show that, under the conditional independence assumption, weighting observations by $\widehat{p}(X)/\left(1-\widehat{p}(X)\right)$ for the control units, where $\widehat{p}(X)$ is a consistent estimator of $p(X)$, and by unity for the treated units, leads to an efficient estimator of the ATT. The intuition is that the control households with observables very similar to the treated households are assigned higher weights, while those relatively more dissimilar are assigned lower weights. The weighs function is given by

$$\omega(t, X) = t + (1-t)\,\frac{\widehat{p}\,(X)}{1-\widehat{p}\,(X)}. \tag{23}$$

The construction of the weights ensures that, under the conditional independence assumption, requiring t_j and ε_{ij} to be independent, the observed predictors of treatment X_j are uncorrelated with t_j and, hence, the weighted estimator is consistent.

Similarly to Blattman and Annan (2010) we follow Imbens (2004) suggestion of combining weighting methods and regression methods with fixed effects or added covariates. This is particularly useful to evaluate the impact of the treatment but also of other covariates and their interactions. In particular, we estimate the following equation:

$$Y_{ij} = \beta_0 + \beta_1 t_j + \beta_2 t_j \alpha_{ij} + \beta_3 Z_{ij} + \varepsilon_{ij}, \tag{24}$$

where Y_{ij} refers to the labor search behavior of individual i in household j, t_j denotes the treatment, defined as the household j having received at least one microfinance loan since 2010, and α_{ij} is a proxy for individual i's within-household bargaining power. Individual and household level controls are collected in Z_{ij}, which also includes the individual's bargaining power α_{ij} (see bottom of Table 5 for a complete list of the control variables).

Testing Proposition 1 and, in particular, Equation (20) boils down to testing the null hypothesis that β_2 is positive. A positive and significant β_2 would confirm the presence of heterogeneous treatment effects, increasing in the bargaining power of the unemployed. In turn, as implied by the first part of Proposition 1, we have no

[21]We check the sensitivity of our results to deviations from the conditional independence assumption (CIA) by simulating a potential confounder in order to assess the robustness of the estimated treatment effects following the methodology proposed by Ichino et al. (2008). The estimated ATT with various specifications for the confounding factors change by less than 5% from the baseline findings.

Table 4: Multinomial probit model at the household level (first stage)

	MFI Loan (1)		Bank Loan (2)	
# of hh members	0.103	(0.081)	0.267***	(0.087)
# of children 15 or younger	0.080	(0.131)	-0.227	(0.142)
Hh owns house	−0.613**	(0.307)	0.636	(0.421)
Hh 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 - 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.

theoretical prediction concerning the sign of β_1. Nonetheless, estimating precisely β_1 is important as it has implications in terms of how the current targeting of credit to poor households contributes to improving labor market outcomes.

5 Microfinance and Job Search: Empirical Findings

We now turn to the empirical analysis to compare the theoretical predictions of our model with the data. The first step, described in Section 5.1 is to model the probability of receiving a microfinance loan at the household level and estimate the propensity scores. Then, in Section 5.2, we use the propensity scores as weights in the individual level regressions, with weights as in Equation (23).

5.1 First Stage: Estimation of the Propensity Scores

Our focus is on borrowing by the poor (the households targeted by the MFI). Hence, we exclude the households that borrow from conventional banks when we estimate Equation (24). However, to have a complete model of access to credit it is important in the first stage to include the households borrowing from conventional banks and to distinguish them from households who borrow from the MFI. Excluding borrowing from conventional banks in the first stage would lead to a biased estimation of the propensity score due to model miss-specification.[22] Therefore, we estimate a multinomial probit model allowing for three possible household statuses: receiving a loan from an MFI, receiving a loan from a bank and not receiving any loan.[23]

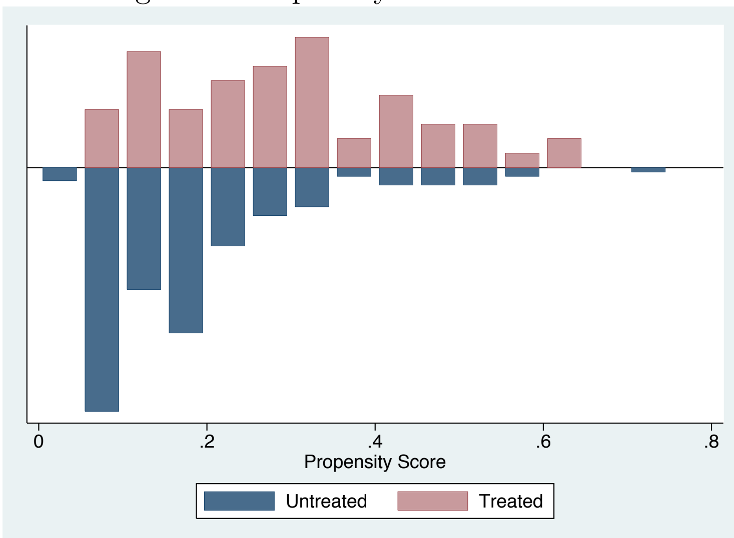
As explained in the previous Section, the identification of the causal impact of the treatment is based on the assumption that allocation of the treatment is purely random among households with the same estimated propensity score, conditional on the pre-treatment characteristics. Hence, the participation equation includes variables that control for the participation and outcomes of interest but are not affected by the treatment. The estimated model is shown in Table 4.

The propensity score estimation enables us to predict the probability of getting access to microcredit at the household level. Figure 2 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. However, to better enforce the common support condition, in what follows we exclude individuals in treated households whose household's probability of treatment exceeds the maximum probability among the untreated households and individuals in the untreated households whose probability of participating is bellow the minimum probability of participation of treated households. The upshot is that we keep observations with propensity scores such that $0.038 \leq \widehat{p}(x) \leq 0.704$.

[22]For example, households without loans but that would if they wanted be able to borrow from conventional banks have very different characteristics than poor households unable to borrow. It is, therefore, important to include borrowing from a conventional banks as a possible household status when modeling access to credit.

[23]While being computationally heavier, the multinomial probit model is based on weaker assumptions than the multinomial logit. In particular, it does not rely on the independence of irrelevant alternatives assumption which allows for the correlation of household access to each available category. See Imbens (2000), Lechner (2001) and Caliendo and Kopeinig (2008) for a discussion of modeling propensity scores in multiple discrete dependent variables settings.

Figure 2: Propensity score distribution



5.2 Second Stage: Labor Search Model

We now turn to the estimation of the main regression equation (24). Our survey asks households if they have ever received a microfinance loan, how many times and when. The treated group, $t_j = 1$, are those households that received at least one microfinance loan since 2010. We exclude from the sample the households who received the last loan earlier because they may no longer have access to microfinance.[24] In turn, households who never had any loan are used to form the control group, for which $t_j = 0$. We are left with 262 unemployed individuals distributed among 191 households.

The dependent variable, Y_{ij}, is the job search effort by the unemployed. We use three alternative measures of labor search effort.[25] Firstly, we use a discrete variable taking value 1 if the unemployed individual has taken any initiative to find a job in the previous four weeks and 0 otherwise. We call the regression equation with this dependent variable Model 1. Secondly, we use an ordered discrete variable capturing the intensity of labor search, denoted Model 2. Finally,

[24] In the model, unemployed workers may decide to search more intensively to raise the household's net-worth and lower the size of the loan needed to be able to invest. So the treated households are those that are going to borrow from an MFI. Instead, given the nature of our survey we must identify the treated households as those who have already borrowed from an MFI. We think this is justified because the typical use of the MFI loans is to finance working capital (see Table 3), and households have repeated interaction with the MFI institution. Thus, households who have borrowed in the past are likely to borrow again so that the net-worth channel described in the model is relevant. However, if the household did not borrow from an MFI for a long time, this assumption is no longer appropriate. This is why we exclude households that did not borrow from an MFI since before 2010.

[25] See footnote 17.

we use an ordered discrete variable corresponding to the number of initiatives taken to search for a job, denoted Model 3.

We want to test Proposition 1 and, in particular, Equation (20) predicting that the search intensity of an unemployed member of a household with an MFI loan compared to that of an unemployed in a household with no loan increases in the individual's bargaining power α_{ij}. But bargaining power is unobservable and, hence, must be proxied by some observable variables. The literature has proposed several measures of bargaining including income, employment, asset ownership and assets brought to marriage.[26] In our context, we must also make sure that our measure of bargaining power is exogenous and, in particular, unaffected by the treatment.[27] Therefore, we select only pre-determined variables as measures of bargaining power.

We use the following variables: *Household size*, which we assume to be negatively correlated with bargaining power since, all else equal, the larger the household, the lower the share of resources received by each member; *Gender*, which, in line with numerous studies of intra-household resource allocation, should capture the disadvantages often faced by women; *Schooling*, which we assume to be negatively correlated with bargaining power since human capital affects not only individual consumption but also their outside option; *Father's schooling*, which we assume is positively correlated with the bargaining power of their offspring, for instance, in the marriage market; *Role of the individual in the household*, since we expect the head of the household to have a higher bargaining power.

5.3 Access to Credit and Job Search: Baseline Findings (Model 1)

We now turn to the paper's main empirical findings. Table 5 shows the results of Model 1. For all regressions reported below we account for dependence between observations by computing robust standard errors. We first estimate the model without re-weighting and without allowing for heterogeneity in the treatment effects, reported in Column 1. This amounts to estimating a standard Probit model. We compare the estimated coefficient β_1 with the one obtained using the inverse probability weighting (IPW), reported in Column 2. While the unweighted β_1 coefficient is positive (but not statistically significant), the IPW estimate is negative and statistically significant and, hence, there is evidence of a

[26] Several of these proxys are discussed in, for example, Lundberg and Pollak (1996), Quisumbing and de la Brière (2000), Friedberg and Webb (2006) and Doss (2013).

[27] Something which we do not explore in this paper is how bargaining power is determined. However, the bargaining power of each household member is likely not invariant to the set of investment opportunities available to each member. This point is made by Tassel (2004). For this reason, in the empirical investigation we only consider pre-determined measures of bargaining power.

positive selection bias. This is what we would expect if, for example, the MFI are able to select households where the unemployed are more diligent in searching for work. The sign of the IPW coefficient implies that the average treatment effect of MFI lending on the incentives for job search by the unemployed is negative. However, given Proposition 1, we are especially interested in the heterogeneity in treatment effects, which is what we look at next.

We allow for heterogeneous treatment effects by interacting the treatment variable with our proxies for bargaining power (Columns 3 to 7). There is robust evidence of heterogeneous treatment effects consistent with Proposition 1. All interaction coefficients are significant and of the expected sign. Being a woman, as well as being a member of a larger household, which are both associated with smaller bargaining power, lower the treatment effect. Instead the effects of own schooling and father's schooling, and of being the household head, each associated with a larger bargaining power, is positive and precisely estimated. For all except one specification (in Column 3), the coefficient β_1 is estimated to be negative, indicating a negative average treatment effect of improved access to credit on search effort by the unemployed.

These findings suggest that there is scope for improving labor market outcomes by better targeting microfinance programs. In particular, improving the access to credit by households whose unemployed members are more likely to exhibit positive treatment effects on job search, which are those with stronger bargaining power, can potentially improve aggregate labor market outcomes in frictional markets. This is a hitherto unexplored channel through which microfinance may have aggregate benefits.

A potential caveat in interpreting our findings is that we only sample individuals currently unemployed. There may be individuals who were unemployed at the time of the loans but that have since found work. In expectation these are the individuals who raise their search effort by a greater amount following the treatment. The upshot is that if the treatment effect is positive, our estimate would be downward biased. Similarly, if the treatment effect is negative we would undersample individuals from the control group and our estimate would be upward biased. Thus, the magnitude of our estimated ATT may suffer from an attenuation bias and as such should be interpreted as a lower bound on the magnitude of the ATT.[28]

[28] We check the sensitivity of our results to deviations from the conditional independence assumption (CIA) by simulating a potential confounder in order to assess the robustness of the estimated treatment effects following the methodology proposed by Ichino et al. (2008). The estimated ATT with various specifications for the confounding factors change by less than 5% from the baseline findings.

Table 5: Access to microcredit and labor search (Model 1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MFI	0.026	−0.932**	0.830	−0.279	−2.097***	−2.868***	−0.905**	−1.024**
	(0.310)	(0.446)	(0.806)	(0.486)	(0.730)	(0.613)	(0.438)	(0.416)
MFI × Household Size			−0.268**					
			(0.106)					
MFI × Female (dummy)				−1.002*				
				(0.583)				
MFI × Schooling (years)					0.179**			
					(0.070)			
MFI × Father School (dummy)						2.906***		
						(0.668)		
MFI × Head (dummy)							2.559***	
							(0.959)	
MFI × Bargaining Power PC								0.981***
								(0.355)
Household size	0.155**	0.183**	0.319***	0.170*	0.167**	0.165*	0.146*	0.133
	(0.066)	(0.090)	(0.109)	(0.089)	(0.084)	(0.085)	(0.084)	(0.087)
Female (dummy)	−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)
Schooling (years)	−0.002	0.054	0.046	0.064	−0.035	0.063	0.035	0.007
	(0.031)	(0.046)	(0.046)	(0.045)	(0.051)	(0.045)	(0.047)	(0.048)
Father School (dummy)	−0.035	−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)
Head (dummy)	−0.055	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)
Unemp. duration: 7 - 12 m	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)
Unemp. 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)
Unemp. duration: > 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 hh. level controls	yes	yes	yes	yes	yes	yes	yes	yes
Other ind. level controls	yes	yes	yes	yes	yes	yes	yes	yes
Neighborhood FE	yes	yes	yes	yes	yes	yes	yes	yes
Inv 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.
Additional household level controls: House ownership (dummy), Number of household members<15, Contacts with family abroad (dummy) and Number of times per week reads journal (dummy). Additional individual level controls: Age, Age2, Country or Island of Origin, Parent Self-Employed (dummy), Number of children, Ownership of Bank Account (dummy) and an indicator for whether the member received the loan (dummy).

Table 6: Access to microcredit and labor search (Model 2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MFI	−0.060	−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 × Household Size			−0.349***					
			(0.116)					
MFI × Female (dummy)				−1.140**				
				(0.569)				
MFI × Schooling (years)					0.199***			
					(0.065)			
MFI × Father School (dummy)						3.048***		
						(0.640)		
MFI × Head (dummy)							1.397*	
							(0.836)	
MFI × Bargaining Power PC								1.201***
								(0.376)
Household size	0.012	−0.117	0.016	−0.109	−0.104	−0.094	−0.128	−0.124
	(0.055)	(0.089)	(0.098)	(0.089)	(0.083)	(0.0818)	(0.0865)	(0.0845)
Female (dummy)	−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)
Schooling (years)	0.024	0.084**	0.070*	0.094**	−0.004	0.080**	0.066	0.032
	(0.027)	(0.041)	(0.040)	(0.040)	(0.046)	(0.039)	(0.041)	(0.041)
Father school (dummy)	0.113	0.089	−0.322	−0.032	0.087	−1.245***	0.138	−0.351
	(0.191)	(0.298)	(0.307)	(0.303)	(0.291)	(0.360)	(0.297)	(0.309)
Head (dummy)	−0.032	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)
Unemp. duration: 7 − 12 m	0.601**	−0.053	−0.025	−0.081	0.521	0.099	0.043	0.387
	(0.276)	(0.410)	(0.416)	(0.391)	(0.421)	(0.388)	(0.385)	(0.412)
Unemp. 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)
Unemp. duration: > 4 y	−0.562**	−0.188	−0.035	−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 hh. level controls	yes	yes	yes	yes	yes	yes	yes	yes
Other ind. level controls	yes	yes	yes	yes	yes	yes	yes	yes
Neighborhood FE	yes	yes	yes	yes	yes	yes	yes	yes
Inv 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.
Additional household level controls: House ownership (dummy), Number of household members<15, Contacts with family abroad (dummy) and Number of times per week reads journal (dummy). Additional individual level controls: Age, Age2, Country or Island of Origin, Parent Self-Employed (dummy), Number of children, Ownership of Bank Account (dummy) and an indicator for whether the member received the loan (dummy).

Table 7: Access to microcredit and labor search (Model 3)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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 × Household Size			−0.130					
			(0.097)					
MFI × Female (dummy)				−0.897				
				(0.613)				
MFI × Schooling (years)					0.081			
					(0.078)			
MFI × Father School (dummy)						2.408***		
						(0.604)		
MFI × Head (dummy)							1.698**	
							(0.698)	
MFI × Bargaining Power PC								0.697**
								(0.353)
Household size	0.053	−0.033	0.022	−0.0223	−0.031	−0.016	−0.058	−0.039
	(0.055)	(0.068)	(0.0816)	(0.067)	(0.067)	(0.065)	(0.069)	(0.066)
Female (dummy)	−0.598***	−0.297	−0.175	0.009	−0.348	−0.096	−0.238	−0.279
	(0.195)	(0.300)	(0.292)	(0.308)	(0.310)	(0.299)	(0.308)	(0.305)
Schooling (years)	0.023	0.053	0.047	0.061	0.016	0.051	0.036	0.021
	(0.025	(0.041)	(0.042)	(0.039)	(0.046)	(0.040)	(0.041)	(0.043)
Father School (dummy)	0.006	0.054	−0.082	−0.082	0.053	−1.041***	0.053	−0.206
	(0.178)	(0.234)	(0.234)	(0.259)	(0.235)	(0.300)	(0.229)	(0.255)
Head (dummy)	0.025	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)
Unemp. duration: 7 − 12 m	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)
Unemp. 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)
Unemp. duration: > 4 y	−0.494**	−0.038	−0.022	−0.040	−0.047	−0.036	−0.201	0.017
	(0.244)	(0.408)	(0.417)	(0.412)	(0.412)	(0.409)	(0.414)	(0.429)
Other hh. level controls	yes	yes	yes	yes	yes	yes	yes	yes
Other ind. level controls	yes	yes	yes	yes	yes	yes	yes	yes
Neighborhood FE	yes	yes	yes	yes	yes	yes	yes	yes
Inv 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.
Additional household level controls: House ownership (dummy), Number of household members<15, Contacts with family abroad (dummy) and Number of times per week reads journal (dummy).Additional individual level controls: Age, Age2, Country or Island of Origin, Parent Self-Employed (dummy), Number of children, Ownership of Bank Account (dummy) and an indicator for whether the member received the loan (dummy).

5.4 A Composite Measure of Intra-household Bargaining Power

Each of our proxies for bargaining power captures a different underlying feature of the intra-household distribution of resources and is, therefore, a partial measure. In order to construct a more comprehensive measure of bargaining power, we use a Principal Component Analysis (PCA) that aggregates the information scattered in the different variables we used (Pearson, 1901; Hotelling, 1933).[29] Since, for the PCA method to be valid, the included variables should have a multivariate normal distribution (or at least be continuous), and since we want to include a combination of dichotomous and continuous variables (gender, own and father's schooling, age, and household size), we perform a polychoric correlation analysis (Kolenikov and Angeles, 2004).

This is implemented as follows. The pairwise correlations between 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. This allows us to run a principal component analysis on the resulting correlation matrix and interpret the first principal component as an index of bargaining power. For Model 1, results are presented in Column (8) of Table 5 and confirm the theoretical predictions: the treatment effect on job search intensity is increasing with the intra-household bargaining power of the unemployed worker.

5.5 Alternative Measures of Search Effort (Model 2 and 3)

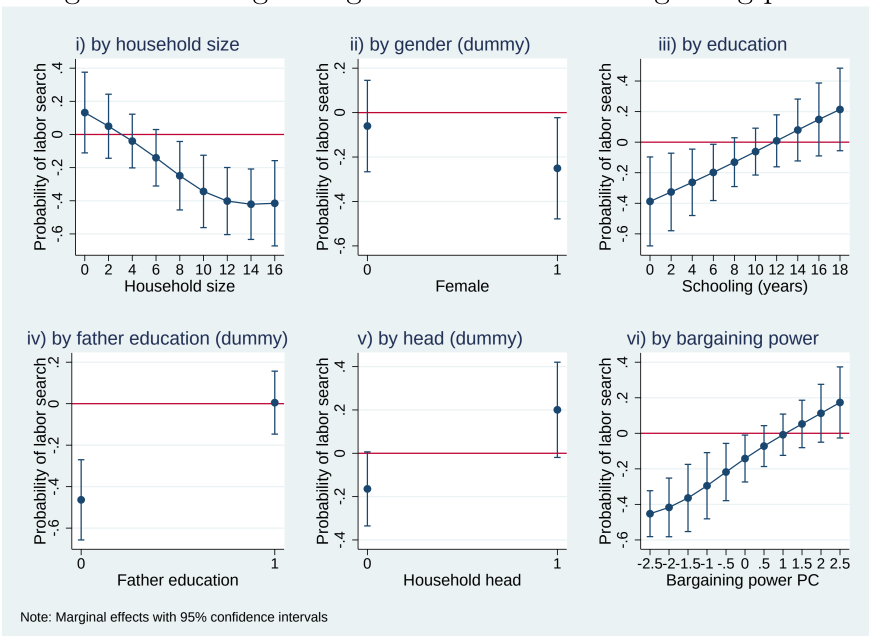
Next, we replicate the empirical analysis with our alternative measures of job search effort: the labor search intensity (Model 2) and the number of labor search initiatives (Model 3).

The estimation results from Model 2 are shown in Table 6. In this case, the dependent variable is an ordered discrete indicator of the intensity of job search, hence we run an ordered Probit model. In turn, the specification of the regression equation and the computation of the regression weights are as in the baseline model. Looking at the weighted regression estimates of the coefficient β_2 for each measure of bargaining power, the estimated coefficient have the same sign and are precisely estimated.

Finally, in Model 3, we use as a dependent variable the discrete indicator of the number of job-search initiatives undertaken by the unemployed. The results are shown in Table 7. The precision of the estimates for this specification is lower. Nonetheless, the evidence of heterogeneous treatment effects remains consistent

[29]See Filmer and Pritchett (2001) for an early and influential paper in development economics and population studies constructing socio-economic indices using PCA.

Figure 3: Average marginal effects across bargaining power



with Proposition 1, in particular for the schooling of the father, the dummy indicating that the individual is the head of the household and the composite measure of bargaining power. We conclude that the evidence of heterogeneous treatment effects consistent with the theoretical prediction are robust to changes in the measure of search effort.

5.6 Discussion of the Results: Marginal Effects

To gain a better sense of the magnitude of the heterogeneous treatment effects estimated under the baseline specification (Model 1), we compute the marginal effect of each interaction term. These are shown in Figure 3, together with their confidence intervals.

Each panel shows the treatment effect on job search as the bargaining power, measured by each proxy, changes. The upper left panel reports the marginal effect on job search as the individual's household size increases. The maintained assumption is that, all else equal, an unemployed individual in a large household receives a low share of resources and, hence, has a lower decision weight α_{ij}. Thus, the figure demonstrates that the treatment effect varies with household size in a way which is consistent with the theoretical prediction. Receiving an MFI loan lowers the probability of unemployed workers searching for jobs if the household size is greater than 3. The estimated negative marginal effect is statistically significant for unemployed individuals living in household of 8 members or more.

Table 8: Bargaining proxys distribution among individuals of treated households

	Percentile				
	5%	25%	50%	75%	95%
Household size	3	5	6	7	12
Gender	man	man	woman	woman	woman
Years of schooling	0	4	9	12	12
Father went to school?	no	no	yes	yes	yes
Unemployed head of household?	no	no	no	no	yes

Selected percentiles for the sample of treated households (those receiving a microfinance loan).
The number of unemployed individuals in treated households is 45, roughly 17% of the sample.

Table 8 shows the distribution of each bargaining power proxy among the treated households. This information allows measuring the fraction of households that borrow from an MFI and with unemployed members for which the treatment is predicted to raise job search. For instance, only around 5% of the households with an MFI loan have fewer than 4 members. Thus, in most treated households, everything else equal, the bargaining power of the unemployed individuals is judged low because of the large household size. The upshot is that for those individuals, the treatment effect on job search effort is negative. The implications of this result for the optimal design of microfinance programs are interesting. The size of the household and, in particular, the number of children may be positively correlated with poverty. Hence, targeting large families may be desirable for the MFI with social objectives.[30] However, our results suggest that by targeting loans to smaller households, the contribution of microfinance to improving aggregate labor market outcomes would be raised. This is because the relative bargaining power of each individual is higher in smaller sized families.

The same analysis can be conducted for each measure of bargaining power. For example, considering gender, the second panel of Figure 3 shows that if the unemployed worker is a woman, receiving an MFI loan lowers the probability of job search by 20 percentage points. If, instead, the man is unemployed, the effect of receiving a loan on the job search is negligible. This is, once again, exactly what is predicted by Proposition 1 if we assume that woman have on average a lower intra-household bargaining power. But, Table 8 shows that more than 50% of the treated households have unemployed workers who are women. For those households, receiving a loan lowers the job search by the unemployed members in the household. Once again, there is scope to improve targeting to support

[30]On the other hand, there is some evidence that larger families are not necessarily poorer. For instance, Lanjouw and Ravallion (1995) show that taking into account scale economies can substantially lower poverty estimates among large families. Instead, Alkire and Santos (2014) shows that poor households are indeed likely to have more children.

better aggregate labor market outcomes: targeting lending to households in which women are (self-) employed and men are unemployed. This would support the entrepreneurial activity of the household and at the same time raise the incentive for job search by the husband.

The heterogeneity in treatment effects is striking when we compare unemployed workers who are the head of the household to those who are not. If the household head is unemployed, receiving an MFI loan is associated with a 20 percentage points increase in the probability of job search. If, instead, the unemployed is not the head of household, the treatment lowers the probability of job search by 20 percentage points.[31] Looking at Table 8, the targeting seems, once again, suboptimal. Only about 5% of unemployed individuals in treated households are the head of household.

Looking at the individual's schooling and father's schooling measures, the findings are as predicted by Proposition1 and the conclusions concerning targeting are very similar.

In the Appendix B we perform several robustness checks, including estimating a linear probability model, clustering the standard errors at the neighborhood level, changing the specification of the first stage model, excluding the households that have defaulted on their MFI loan. Finally, we perform a placebo test, where the treatment is defined as having knowledge of microfinance.

6 Conclusion

We propose a simple collective household choice model in which individual job search in frictional labor markets depends on intra-household bargaining and on access to finance. We show that the impact of access to finance on job search intensity is ambiguous and depends on the interaction between the net-worth and income effects. Moreover, the search intensity of the unemployed workers in households with access to finance relative to those without access is increasing in the individual's bargaining power within the household.

Using several measures of individual intra-household bargaining power, we test the predictions of our model using data collected by the authors in Cape Verde. The data was collected to evaluate the impact of microfinance programs and, therefore, the population of interest are poor households. Our assumptions are general, but we believe that our findings are mostly relevant for poor households, characterized by lack of capital and whose livelihood, in the absence of public welfare schemes, is strongly influenced and supported by family ties. This is the typical target of microfinance programs.

[31] This finding is interesting, as the household role is a clean measure of bargaining power.

Linking access to finance to collective household decision making is important when evaluating the impact of development programs since family links affect the livelihood and the decision making process of the poor very strongly (Platteau, 1991, Fafchamps and Susan, 2003, Collins et al., 2009). Besides contributing to the literature on collective decision making, our results also provide some new and important policy implications for the design of microfinance programs. Microfinance was primarily designed to promote self-employment in those areas of the world where the poor have little or no opportunity to find a job. Our results highlight the importance of rethinking the targeting of microfinance, since relaxing credit constraints to poor households may have complementarities with improved labor market outcomes but may also discourage the supply of wage labor. Which effect prevails, depends on the targeting of loans.

We show that the behavior of unemployed household members is affected by the access to credit in a non-trivial way, potentially undermining the positive effects of microfinance. When poorly targeted, access to finance can lower the incentives to search for work, making the overall impact on welfare ambiguous. Our findings suggest that, to improve the impact of microfinance on labor market outcomes, the screening should not be solely based on the characteristics of the entrepreneurial activity and individual borrower, but also on characteristics of the household she/he belongs to and, in particular, the within-household distribution of decision power. We explore simple indicators of bargaining power that are easy to measure and scrutinize. If they are used to improve targeting, they can improve the impact of access to finance, generating positive externalities in terms of labor market outcomes. A corollary is that to assess the impact of microfinance programs, it is important to focus not only on the direct impact on borrowers, but also on the indirect effects on other family members.

References

Ahlin, C., J. Lin, and M. Maio (2011). Where does microfinance flourish? microfinance institution performance in macroeconomic context. *Journal of Development Economics 95*(2), 105–120.

Alkire, S. and M. E. Santos (2014). Measuring acute poverty in the developing world: Robustness and scope of the multidimensional poverty index. *World Development 59*, 251–274.

Anderson, S. and J.-M. Baland (2002). The economics of roscas and intrahousehold resource allocation. *Quarterly Journal of Economics 117*(3), 963–995.

Angrist, J. D. and J.-S. Pischke (2008). *Mostly harmless econometrics: An empiricist's companion.* Princeton university press.

Ashraf, N. (2009). Spousal control and intra-household decision making: An experimental study in the philippines. *American Economic Review 99*(4), 1245–1277.

Blattman, C. and J. Annan (2010). The consequences of child soldiering. *The Review of Economic Statistics 92*(4), 882–898.

Blundell, R., P.-A. Chiappori, and C. Meghir (2005). Collective labor supply with children. *Journal of Political Economy 113*(6), 1277–1306.

Browning, M., F. Bourguignon, P.-A. Chiappori, and V. Lechene (1994). Income and outcomes: A structural model of intrahousehold allocation. *Journal of Political Economy 102*(6), 1067–1096.

Caliendo, M. and S. Kopeinig (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys 22*(1), 31–72.

Callen, M., S. D. Mel, C. McIntosh, and C. Woodruff (2014). What are the headwaters of formal savings? experimental evidence from sri lanka. Working Paper 20736, National Bureau of Economic Research.

Cameron, A. C. and D. L. Miller (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources* (Forthcoming Spring 2015).

Card, D., R. Chetty, and A. Weber (2007). Cash-on-hand and competing models of intertemporal behavior: New evidence from the labor market. *Quarterly Journal of Economics 122*(4), 1511–1560.

Cherchye, L., B. De Rock, and F. Vermeulen (2012). Married with children: A collective labor supply model with detailed time use and intrahousehold expenditure information. *American Economic Review 102*(7), 3377–3405.

Chiappori, P.-A. (1992). Collective labor supply and welfare. *Journal of Political Economy 100*(3), 437–67.

Collins, D., J. Morduch, S. Rutherford, and O. Ruthven (2009). *Portfolios of the Poor: How the World's Poor Live on $2 a Day.* Princeton University Press.

Dehejia, R. H. and S. Wahba (2002). Propensity score-matching methods for nonexperimental causal studies. *Review of Economics and Statistics 84*(1), 151–161.

Doss, C. (2013). Intrahousehold bargaining and resource allocation in developing countries. *The World Bank Research Observer 28*(1), 52–78.

Duflo, E. (2000). Child health and household resources in South Africa: evidence from the old age pension program. *American Economic Review 90*(2), 393–398.

Fafchamps, M. and L. Susan (2003). Risk-sharing networks in rural philippines. *Journal of Development Economics 71*, 261 – 287.

Filmer, D. and L. H. Pritchett (2001). Estimating wealth effects without expenditure data - or tears: An application to educational enrollments in states of india. *Demography 38*(1), 115–132.

Friedberg, L. and A. Webb (2006). Determinants and consequences of bargaining power in households. Technical report, National Bureau of Economic Research.

Heckman, J. J., H. Ichimura, and P. Todd (1998). Matching as an econometric evaluation estimator. *The Review of Economic Studies 65*(2), 261–294.

Hirano, K., G. W. Imbens, and G. Ridder (2003). Efficient estimation of average treatment effects using the estimated propensity score. *Econometrica 71*(4), 1161–1189.

Hotelling, H. (1933). Analysis of a complex of statistical variables into principal components. *Journal of Educational Psychology 24*(6), 417.

Ichino, A., F. Mealli, and T. Nannicini (2008). From temporary help jobs to permanent employment: what can we learn from matching estimators and their sensitivity? *Journal of Applied Econometrics 23*(3), 305–327.

Imbens, G. W. (2000). The role of the propensity score in estimating dose-response functions. *Biometrika 87*(3), 706–710.

Imbens, G. W. (2004). Nonparametric estimation of average treatment effects under exogeneity: A review. *Review of Economics and Statistics 86*(1), 4–29.

Kimball, M. S. (1990). Precautionary saving in the small and in the large. *Econometrica 58*(1), 53–73.

Kolenikov, S. and G. Angeles (2004). The use of discrete data in pca: theory, simulations, and applications to socioeconomic indices. *Chapel Hill: Carolina Population Center, University of North Carolina*.

Lanjouw, P. and M. Ravallion (1995). Poverty and household size. *The Economic Journal 105*, 1415–1434.

Lechner, M. (2001). Identification and estimation of causal effects of multiple treatments under the conditional independence assumption. *Econometric Evaluation of Labour Market Policies 13*, 43.

Lentz, R. and T. Tranas (2005). Job search and savings: Wealth effects and duration dependence. *Journal of Labor Economics 23*(3), 467–490.

Lundberg, S. and R. A. Pollak (1996). Bargaining and distribution in marriage. *Journal of Economic Perspectives*, 139–158.

Morduch, J. (1998). Does microfinance really help the poor?: New evidence from flagship programs in bangladesh. Mimeo.

Ngo, T. M.-P. and Z. Wahhaj (2012). Microfinance and gender empowerment. *Journal of Development Economics 99*(1), 1–12.

Pearson, K. (1901). On lines and planes of closest fit to systems of points in space. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science 2*(11), 559–572.

Pitt, M. M. and S. R. Khandker (1998). The impact of group-based credit programs on poor households in Bangladesh: Does the gender of participants matter? *Journal of Political Economy 106*(5), 958–996.

Platteau, J.-P. (1991). Traditional systems of social security and hunger insurance: past achievements and modern challenges. In E. Ahmad, J. Dreze, J. Hills, and A. Sen (Eds.), *Social Security in Developing Countries*. Clarendon Press, Oxford.

Quisumbing, A. R. and B. de la Brière (2000). Women's assets and intrahousehold allocation in rural Bangladesh : Testing measures of bargaining power. FCND discussion papers 86, International Food Policy Research Institute.

Rosenbaum, P. R. and D. B. Rubin (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician 39*(1), 33–38.

Schaner, S. G. (2013). The cost of convenience? transaction costs, bargaining power, and savings account use in kenya. Mimeo.

Smith, J. A. and P. E. Todd (2005). Does matching overcome lalonde's critique of nonexperimental estimators? *Journal of Econometrics 125*(1-2), 305–353.

Tassel, E. V. (2004). Household bargaining and microfinance. *Journal of Development Economics 74*(2), 449–468.

Thomas, D. (1990). Intra-household resource allocation: An inferential approach. *Journal of Human Resources 25*(4), 635–664.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data.* MIT press.

World Bank (2007). A dinámica da pobreza em cabo verde. Technical report, The World Bank.

A Taylor expansion of $\Delta(C_e, C_n; t)$

In the main text, we use the first order Taylor expansion of $\Delta(C_e, C_n; t)$ around the point

$$\{C_e^\bullet(t), C_n^\bullet(t)\} = \left\{(1+f(\alpha))^{-1} Y_n(t), (1+f(\alpha))^{-1} Y_n(t)\right\}.$$

This is given by

$$\begin{aligned}\Delta(C_e, C_n; t) \approx\ & \hat{u}(C_e^\bullet(t)) - \hat{u}(C_n^\bullet(t)) + \\ & \hat{u}'(C_e^\bullet(t))[C_e(t) - C_e^\bullet(t)] - \hat{u}'(C_n^\bullet(t))[C_n(t) - C_n^\bullet(t)],\end{aligned} \tag{A.1}$$

where

$$C_e^\bullet(t) = C_n^\bullet(t) = (1+f(\alpha))^{-1} Y_n(t). \tag{A.2}$$

Using the budget constraint (10) we have that

$$C_n(t) = (1+f(\alpha))^{-1} Y_n(t) = C_n^\bullet(t), \tag{A.3}$$

$$\begin{aligned}C_e(t) &= (1+f(\alpha))^{-1} Y_e(t) \\ &= \begin{cases} C_e^\bullet(1) + (1+f(\alpha))^{-1}(1+r)W, & t=1 \\ C_e^\bullet(0) + (1+f(\alpha))^{-1} W, & t=0 \end{cases}\end{aligned} \tag{A.4}$$

Using (A.2), (A.3) and (A.4) to substitute in (A.1) yields

$$\Delta(C_e, C_n; t) \approx$$

$$\widetilde{\Delta}(\alpha; t) = \begin{cases} \hat{u}'\left((1+f(\alpha))^{-1} Y_n(1)\right)\left[(1+f(\alpha))^{-1}(1+r)W\right], & t=1 \\ \\ \hat{u}'\left((1+f(\alpha))^{-1} Y_n(0)\right)\left[(1+f(\alpha))^{-1} W\right], & t=0 \end{cases} \tag{A.5}$$

which corresponds to equation (14) in the main text.

B Appendix: Robustness Tests

In this Appendix we investigate the robustness of our findings to: alternative estimation model; alternative construction of the standard errors, changes in model specification; changes in the sample. In particular, we estimate a linear probability model, we try clustering the standard errors at the neighborhood level, we change the specification of the first stage model, and we change the sample by excluding the households that have defaulted on their MFI loan. Finally, we perform a placebo test, where the treatment is defined as having knowledge of microfinance.

B.1 Linear Probability Model

As a first robustness check, we repeated the analysis using a linear probability model (LPM), estimated by Ordinary Least Squares (OLS). If the true conditional expectation function is unknown, it is helpful to contrast the LPM to the Probit model (Wooldridge, 2010). The estimation results are reported in Table A1 and the corresponding marginal effects in Figure A1. Comparing marginal effects, we can see that for all measures of bargaining power considered, the significance and general trends are very similar for both models.

B.2 Clustering of Standard Errors at the Neighborhood Level

Second, in Table A2 and Figure A2 we take into account the fact that the standard errors may be correlated within neighborhoods. Clustering the standard errors at the neighborhood level does not alter the results in any significant way.[32]

B.3 Alternative First Stage Model

Third, since ATT estimated with propensity score methods can be sensitive to specifications of the matching model (see Smith and Todd, 2005, and Heckman et al., 1998), we estimate the model using alternative sets of covariates in the first stage.[33] In particular, we include higher order variables (the square of household size and number of children) and remove the neighborhood fixed effects. The results of this alternative specification are displayed in Table A3 and Figure A3 and are qualitatively and quantitatively very similar to our baseline specification.

B.4 Excluding Defaulting Households

As a fourth robustness check, we exclude from the sample the few households which defaulted on their microfinance loans, which reduces our sample to 259 observations. Our motivation in doing this is to fully align the empirical analysis with the assumptions of the theoretical model. In fact, in Section 2, we assume that households know they have access to finance when deciding on the search intensity. In our baseline specification, we took this into account by restricting the sample to loans given since 2010. Now, we further refine the sample excluding

[32]In our main specification (Model 1, Model 2 and Model 3), we chose not to cluster standard errors and only use neighborhood fixed effects since clustering can be misleading in the case of few clusters (Angrist and Pischke, 2008). Moreover, the fixed effects and control variables should absorb most of the systematic within-cluster correlation (Cameron and Miller, 2015).

[33]Dehejia and Wahba (2002) advocate this type of checks in the absence of an experimental benchmark estimate.

the 'bad' clients. Since MFI usually have repeated interactions with their clients, it is likely that recent clients and clients that did not default have much easier access to microfinance.[34] Reassuringly, the results are again consistent with our baseline results and our theoretical prediction (see Table A4 and Figure A4).

B.5 Placebo Test

Finally, we perform a placebo test to evaluate whether the relationship we have estimated is induced by some other mechanism underlying the characteristics of our covariates and not by the mechanisms we have outlined. In particular, we replace the dummy treatment variable *MFI* capturing the fact that households had access to microfinance, by the dummy variable *Heard about microfinance*, capturing whether households know what microfinance is. We expected this placebo treatment not to have predictive power on the dependent variable, the probability of Job Search. Table A5 and Figure A5 show that, as expected, the placebo treatment, interacted with measures of bargaining power, has no significant impact on the job search of the unemployed.

[34] Our definition of default (loan not repaid 3 months after the due date), is in general stricter than the one used by Cape Verdean MFI in their operations. When deciding whether a clients is eligible for more credit, soft information available to credit officers plays a crucial role, so loans can be given out also to clients who repaid with significant, but "justified", delays.

Table A1: Access to microcredit and labor search: OLS regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MFI	0.034	−0.194*	0.091	−0.004	−0.469***	−0.591***	−0.185*	−0.245**
	(0.094)	(0.116)	(0.194)	(0.111)	(0.209)	(0.165)	(0.109)	(0.115)
MFI × Household Size			−0.042*					
			(0.023)					
MFI × Female (dummy)				−0.322**				
				(0.160)				
MFI × Schooling (years)					0.038**			
					(0.019)			
MFI × Father School (dummy)						0.612***		
						(0.174)		
MFI × Head (dummy)							0.351	
							(0.225)	
MFI × Bargaining Power PC								0.216**
								(0.087)
Household size	0.040**	0.0203	0.040*	0.023	0.020	0.025	0.015	0.017
	(0.018)	(0.022)	(0.023)	(0.021)	(0.020)	(0.019)	(0.022)	(0.020)
Female	-0.194***	-0.116	-0.085	-0.005	-0.137*	-0.0508	-0.102	-0.104
	(0.065)	(0.072)	(0.075)	(0.080)	(0.076)	(0.0711)	(0.0714)	(0.0736)
Schooling (years)	0.004	0.011	0.010	0.012	-0.007	0.007	0.009	-0.002
	(0.009)	(0.011)	(0.011)	(0.010)	(0.013)	(0.011)	(0.011)	(0.012)
Father School (dummy)	-0.005	-0.011	-0.050	-0.063	-0.018	-0.304***	-0.013	-0.101
	(0.064)	(0.078)	(0.075)	(0.085)	(0.077)	(0.091)	(0.076)	(0.079)
Head (dummy)	-0.007	0.292**	0.334***	0.260**	0.194	0.223**	0.168	0.243**
	(0.097)	(0.113)	(0.115)	(0.108)	(0.130)	(0.0981)	(0.171)	(0.107)
Unemp. duration: 7 - 12 m	0.259***	0.025	0.013	0.060	0.154	0.086	0.035	0.148
	(0.095)	(0.113)	(0.112)	(0.102)	(0.117)	(0.114)	(0.111)	(0.112)
Unemp. duration: 1 to 4 y	0.168**	0.095	0.092	0.132	0.095	0.137	0.081	0.126
	(0.068)	(0.085)	(0.082)	(0.083)	(0.087)	(0.093)	(0.085)	(0.093)
Unemp. duration: > 4 y	-0.181**	-0.102	-0.099	-0.094	-0.101	-0.108	-0.138	-0.081
	(0.081)	(0.111)	(0.108)	(0.111)	(0.112)	(0.106)	(0.110)	(0.116)
Other hh. level controls	yes	yes	yes	yes	yes	yes	yes	yes
Other ind. level controls	yes	yes	yes	yes	yes	yes	yes	yes
Neighborhood FE	yes	yes	yes	yes	yes	yes	yes	yes
Inv probability weighting	no	yes	yes	yes	yes	yes	yes	yes
Observations	262	262	262	262	262	262	262	262
Pseudo R-squared	0.346	0.623	0.630	0.634	0.638	0.668	0.630	0.644

Robust standard errors in parentheses, *p<0.10, ** p<0.05, *** p<0.01.
Additional household level controls: House ownership (dummy), Number of household members<15, Contacts with family abroad (dummy) and Number of times per week reads journal (dummy). Additional individual level controls: Age, Age2, Origin, Parent Self-Employed (dummy), Number of children, Ownership of Bank Account (dummy) and an indicator for whether the member received the loan (dummy).

Table A2: Access to credit and labor search: Clustering at neighborhood level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MFI	0.026	-0.932**	0.830	-0.279	-2.097***	-2.868***	-0.905*	-1.024**
	(0.284)	(0.455)	(0.752)	(0.463)	(0.768)	(0.549)	(0.534)	(0.400)
MFI × Household Size			-0.268**					
			(0.108)					
MFI × Female (dummy)				-1.002**				
				(0.504)				
MFI × Schooling (years)					0.179**			
					(0.076)			
MFI × Father School (dummy)						2.906***		
						(0.563)		
MFI × Head (dummy)							2.559***	
							(0.957)	
MFI × Bargaining Power PC								0.981***
								(0.305)
Household size	0.155**	0.183**	0.319***	0.170**	0.167**	0.165*	0.146*	0.133*
	(0.062)	(0.082)	(0.085)	(0.084)	(0.075)	(0.089)	(0.077)	(0.078)
Female	-0.706***	-0.480	-0.298	-0.106	-0.566	-0.513	-0.445	-0.476
	(0.155)	(0.333)	(0.380)	(0.307)	(0.361)	(0.399)	(0.286)	(0.360)
Schooling (years)	-0.002	0.054	0.046	0.064	-0.035	0.063	0.035	0.007
	(0.025)	(0.047)	(0.043)	(0.040)	(0.054)	(0.045)	(0.046)	(0.050)
Father School (dummy)	-0.035	-0.293	-0.470	-0.320	-0.250	-1.621***	-0.307	-0.586*
	(0.290)	(0.317)	(0.360)	(0.340)	(0.294)	(0.332)	(0.329)	(0.304)
Head (dummy)	-0.055	0.935**	1.162***	0.824**	0.722*	0.642	0.526	0.755*
	(0.255)	(0.392)	(0.412)	(0.361)	(0.387)	(0.424)	(0.446)	(0.398)
Unemp. duration: 7 - 12 m	0.868**	0.814	0.670	0.837*	1.070***	0.986**	0.784*	1.128***
	(0.353)	(0.527)	(0.572)	(0.469)	(0.406)	(0.427)	(0.449)	(0.412)
Unemp. duration: 1 to 4 y	0.612*	0.516	0.415	0.562	0.470	0.691**	0.438	0.619*
	(0.339)	(0.392)	(0.430)	(0.346)	(0.405)	(0.338)	(0.414)	(0.347)
Unemp. duration: > 4 y	-0.645*	-0.317	-0.388	-0.330	-0.398	-0.324	-0.471	-0.290
	(0.359)	(0.570)	(0.556)	(0.543)	(0.567)	(0.516)	(0.576)	(0.536)
Other hh. level controls	yes	yes	yes	yes	yes	yes	yes	yes
Other ind. level controls	yes	yes	yes	yes	yes	yes	yes	yes
Neighborhood FE	yes	yes	yes	yes	yes	yes	yes	yes
Inv 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.
Additional household level controls: House ownership (dummy), Number of household members<15, Contacts with family abroad (dummy) and Number of times per week reads journal (dummy). Additional individual level controls: Age, Age2, Origin, Parent Self-Employed (dummy), Number of children, Ownership of Bank Account (dummy) and an indicator for whether the member received the loan (dummy).

Table A3: Alternative specification of the first stage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MFI	0.00886	-0.660	0.884	-0.146	-1.625**	-1.870***	-0.573	-0.776*
	(0.306)	(0.431)	(0.789)	(0.512)	(0.713)	(0.596)	(0.433)	(0.422)
MFI × Household Size			-0.246**					
			(0.100)					
MFI × Female (dummy)				-0.844				
				(0.622)				
MFI × Schooling (years)					0.136**			
					(0.068)			
MFI × Father School (dummy)						1.814***		
						(0.611)		
MFI × Head (dummy)							2.848**	
							(1.129)	
MFI × Bargaining Power PC								0.660*
								(0.352)
Household size	0.132**	0.263***	0.396***	0.276***	0.276***	0.299***	0.225**	0.263***
	(0.057)	(0.081)	(0.106)	(0.095)	(0.091)	(0.094)	(0.090)	(0.0942)
Female	-0.703***	-0.499	-0.202	-0.0991	-0.429	-0.417	-0.404	-0.383
	(0.206)	(0.312)	(0.365)	(0.382)	(0.342)	(0.335)	(0.345)	(0.340)
Schooling (years)	0.017	0.069	0.049	0.069	-0.006	0.052	0.037	0.027
	(0.029)	(0.044)	(0.048)	(0.047)	(0.050)	(0.047)	(0.049)	(0.048)
Father School (dummy)	-0.0585	-0.365	-0.383	-0.225	-0.219	-0.860**	-0.175	-0.395
	(0.205)	(0.268)	(0.280)	(0.281)	(0.279)	(0.343)	(0.279)	(0.298)
Head (dummy)	-0.091	0.739	0.961**	0.697	0.585	0.636	0.239	0.694
	(0.292)	(0.450)	(0.450)	(0.447)	(0.495)	(0.433)	(0.547)	(0.456)
Unemp. duration: 7 - 12 m	0.882***	0.919**	0.658	0.835**	0.887**	0.951**	0.764*	0.968**
	(0.321)	(0.418)	(0.424)	(0.408)	(0.427)	(0.434)	(0.424)	(0.439)
Unemp. duration: 1 to 4 y	0.553***	1.026***	0.919***	1.043***	0.983***	1.142***	1.004***	1.067***
	(0.214)	(0.313)	(0.305)	(0.315)	(0.319)	(0.341)	(0.322)	(0.335)
Unemp. duration: > 4 y	-0.655***	-0.296	-0.375	-0.398	-0.424	-0.252	-0.497	-0.327
	(0.247)	(0.330)	(0.325)	(0.330)	(0.335)	(0.348)	(0.339)	(0.348)
Other hh. level controls	yes	yes	yes	yes	yes	yes	yes	yes
Other ind. level controls	yes	yes	yes	yes	yes	yes	yes	yes
Neighborhood FE	yes	yes	yes	yes	yes	yes	yes	yes
Inv probability weighting	no	yes	yes	yes	yes	yes	yes	yes
Observations	262	262	262	262	262	262	262	262
Pseudo R-squared	0.323	0.638	0.660	0.654	0.659	0.672	0.662	0.659

Robust standard errors in parentheses, *p<0.10, ** p<0.05, *** p<0.01.
Additional household level controls: House ownership (dummy), Number of household members<15, Contacts with family abroad (dummy) and Number of times per week reads journal (dummy). Additional individual level controls: Age, Age2, Origin, Parent Self-Employed (dummy), Number of children, Ownership of Bank Account (dummy) and an indicator for whether the member received the loan (dummy).

Table A4: Microfinance and job search excluding households who defaulted

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MFI	-0.0397	-0.804**	0.908	-0.187	-1.497**	-2.261***	-0.861**	-0.871**
	(0.315)	(0.405)	(0.806)	(0.447)	(0.715)	(0.607)	(0.400)	(0.412)
MFI × Household Size			-0.252**					
			(0.099)					
MFI × Female (dummy)				-0.928				
				(0.567)				
MFI × Schooling (years)					0.101			
					(0.071)			
MFI × Father School (dummy)						2.025***		
						(0.639)		
MFI × Head (dummy)							1.827**	
							(0.761)	
MFI × Bargaining Power PC								0.396
								(0.350)
Household size	0.164**	0.150*	0.265***	0.140*	0.139*	0.151*	0.137*	0.129
	(0.067)	(0.086)	(0.097)	(0.084)	(0.083)	(0.085)	(0.083)	(0.0863)
Female	-0.711***	-0.411	-0.276	-0.063	-0.470	-0.484	-0.388	-0.422
	(0.216)	(0.316)	(0.320)	(0.313)	(0.316)	(0.306)	(0.310)	(0.313)
Schooling (years)	-0.004	0.019	0.018	0.029	-0.025	0.043	0.012	0.004
	(0.031)	(0.047)	(0.046)	(0.046)	(0.050)	(0.046)	(0.047)	(0.047)
Father School (dummy)	-0.059	-0.813***	-0.908***	-0.814***	-0.750**	-1.511***	-0.828***	-0.867***
	(0.219)	(0.305)	(0.298)	(0.294)	(0.310)	(0.383)	(0.304)	(0.306)
Head (dummy)	-0.057	0.618	0.764*	0.528	0.550	0.562	0.357	0.587
	(0.314)	(0.459)	(0.441)	(0.454)	(0.466)	(0.449)	(0.482)	(0.462)
Unemp. duration: 7 - 12 m	0.849***	0.786	0.633	0.800*	0.941*	0.917*	0.793	0.911*
	(0.328)	(0.512)	(0.499)	(0.483)	(0.493)	(0.494)	(0.491)	(0.504)
Unemp. duration: 1 to 4 y	0.583**	0.286	0.203	0.323	0.272	0.511	0.217	0.356
	(0.228)	(0.341)	(0.324)	(0.324)	(0.336)	(0.345)	(0.333)	(0.351)
Unemp. duration: > 4 y	-0.667**	-0.765**	-0.840**	-0.788**	-0.752**	-0.556	-0.850**	-0.688*
	(0.262)	(0.349)	(0.351)	(0.344)	(0.352)	(0.357)	(0.354)	(0.365)
Other hh. level controls	yes	yes	yes	yes	yes	yes	yes	yes
Other ind. level controls	yes	yes	yes	yes	yes	yes	yes	yes
Neighborhood FE	yes	yes	yes	yes	yes	yes	yes	yes
Inv probability weighting	no	yes	yes	yes	yes	yes	yes	yes
Observations	259	259	259	259	259	259	259	259
Pseudo R-squared	0.303	0.494	0.513	0.501	0.501	0.518	0.505	0.498

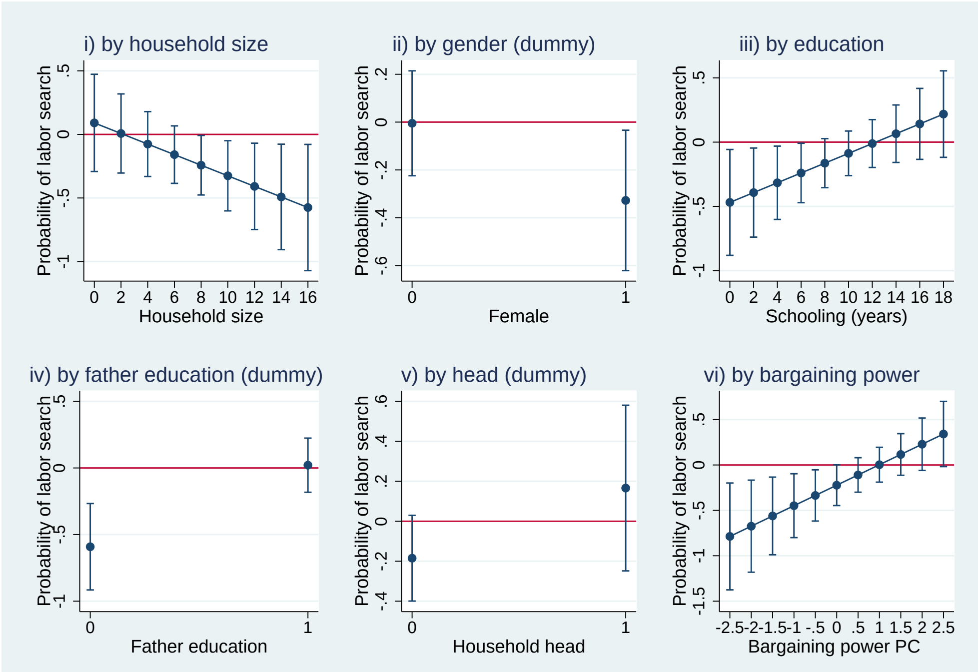
Robust standard errors in parentheses, *p<0.10, ** p<0.05, *** p<0.01.
Additional household level controls: House ownership (dummy), Number of household members<15, Contacts with family abroad (dummy) and Number of times per week reads journal (dummy). Additional individual level controls: Age, Age2, Origin, Parent Self-Employed (dummy), Number of children, Ownership of Bank Account (dummy) and an indicator for whether the member received the loan (dummy).

Table A5: Placebo test: Impact of Having heard about Microfinance on labor search

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Heard about MF	0.142	0.0979	-0.305	-0.202	0.884	0.580	0.104	0.0722
	(0.226)	(0.333)	(0.728)	(0.513)	(0.700)	(0.683)	(0.352)	(0.340)
Heard about MF × Household Size			0.060					
			(0.099)					
Heard about MF × Female				0.448				
				(0.600)				
Heard about MF × Education					-0.131			
					(0.089)			
Heard about MF × Father School (dummy)						-0.732		
						(0.803)		
Heard of MF × Head (dummy)							-0.065	
							(0.653)	
Heard of MF × Bargaining Power PC								-0.404
								(0.332)
Household size	0.152**	0.180**	0.133	0.187**	0.195**	0.165*	0.180**	0.204**
	(0.066)	(0.092)	(0.118)	(0.093)	(0.097)	(0.094)	(0.092)	(0.098)
Female	-0.717***	-0.287	-0.281	-0.634	-0.275	-0.336	-0.286	-0.434
	(0.214)	(0.343)	(0.346)	(0.496)	(0.343)	(0.357)	(0.346)	(0.377)
Schooling (years)	-0.002	0.041	0.042	0.040	0.154*	0.047	0.041	0.088
	(0.031)	(0.046)	(0.046)	(0.046)	(0.082)	(0.047)	(0.046)	(0.057)
Father school (dummy)	-0.052	-0.213	-0.179	-0.203	-0.222	0.313	-0.213	0.022
	(0.216)	(0.302)	(0.311)	(0.298)	(0.300)	(0.675)	(0.303)	(0.374)
Head (dummy)	-0.053	1.160***	1.162***	1.152***	1.185***	1.129**	1.221**	0.802
	(0.312)	(0.448)	(0.446)	(0.446)	(0.449)	(0.451)	(0.574)	(0.517)
Unemp. duration: 7 - 12 m	0.885***	0.798	0.779	0.785	0.841	0.729	0.799	0.782
	(0.323)	(0.543)	(0.555)	(0.553)	(0.556)	(0.539)	(0.542)	(0.547)
Unemp. duration: 1 to 4 y	0.603***	0.433	0.443	0.465	0.447	0.361	0.433	0.408
	(0.230)	(0.324)	(0.329)	(0.326)	(0.330)	(0.327)	(0.324)	(0.320)
Unemp. duration: > 4 y	-0.637**	-0.551	-0.574	-0.524	-0.522	-0.613*	-0.551	-0.546
	(0.253)	(0.357)	(0.368)	(0.355)	(0.359)	(0.354)	(0.357)	(0.355)
Other hh. level controls	yes	yes	yes	yes	yes	yes	yes	yes
Other ind. level controls	yes	yes	yes	yes	yes	yes	yes	yes
Neighborhood FE	yes	yes	yes	yes	yes	yes	yes	yes
Inv probability weighting	no	yes	yes	yes	yes	yes	yes	yes
Observations	262	262	262	262	262	262	262	262
Pseudo R-squared	0.307	0.569	0.570	0.570	0.572	0.571	0.569	0.571

Robust standard errors in parentheses, *p<0.10, ** p<0.05, *** p<0.01.
Additional household level controls: House ownership (dummy), Number of household members<15, Contacts with family abroad (dummy) and Number of times per week reads journal (dummy). Additional individual level controls: Age, Age2, Origin, Parent Self-Employed (dummy), Number of children, Ownership of Bank Account (dummy) and an indicator for whether the member received the loan (dummy).

Figure A1: Average marginal effects in the linear probability model



Note: Marginal effects with 95% confidence intervals

Figure A2: Average marginal effects with clustering at neighborhood level

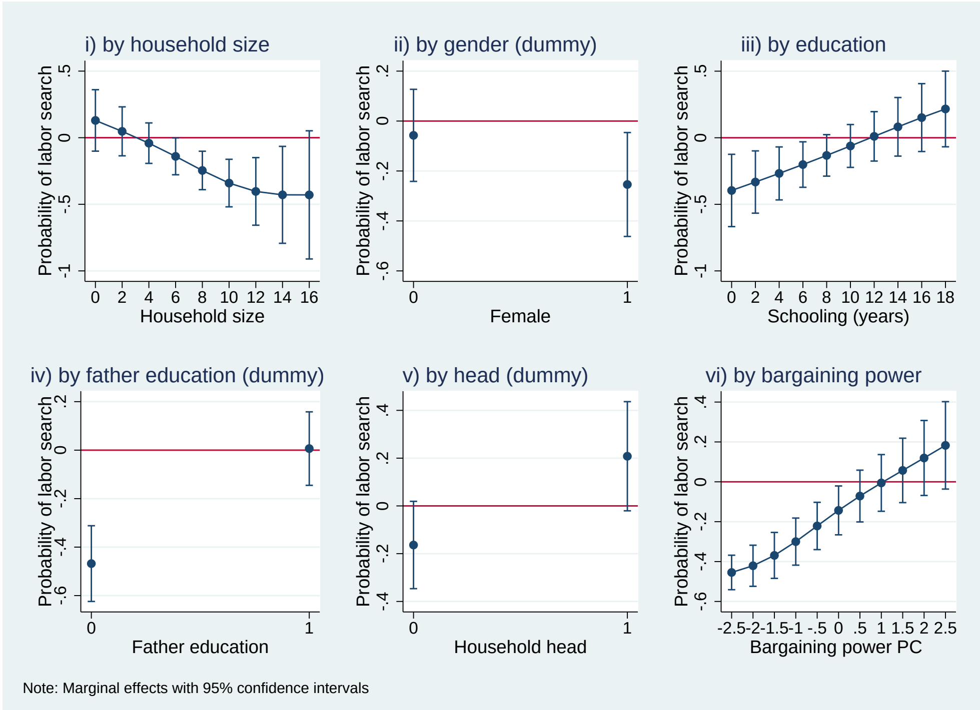


Figure A3: Alternative specification of the first stage

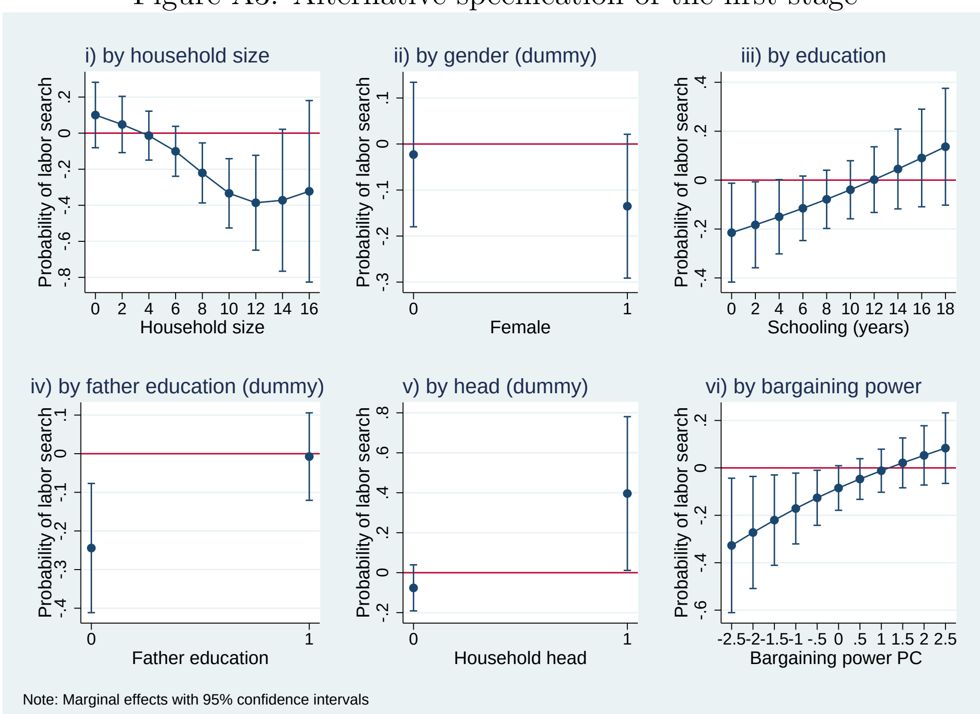


Figure A4: Average marginal effects excluding households who defaulted

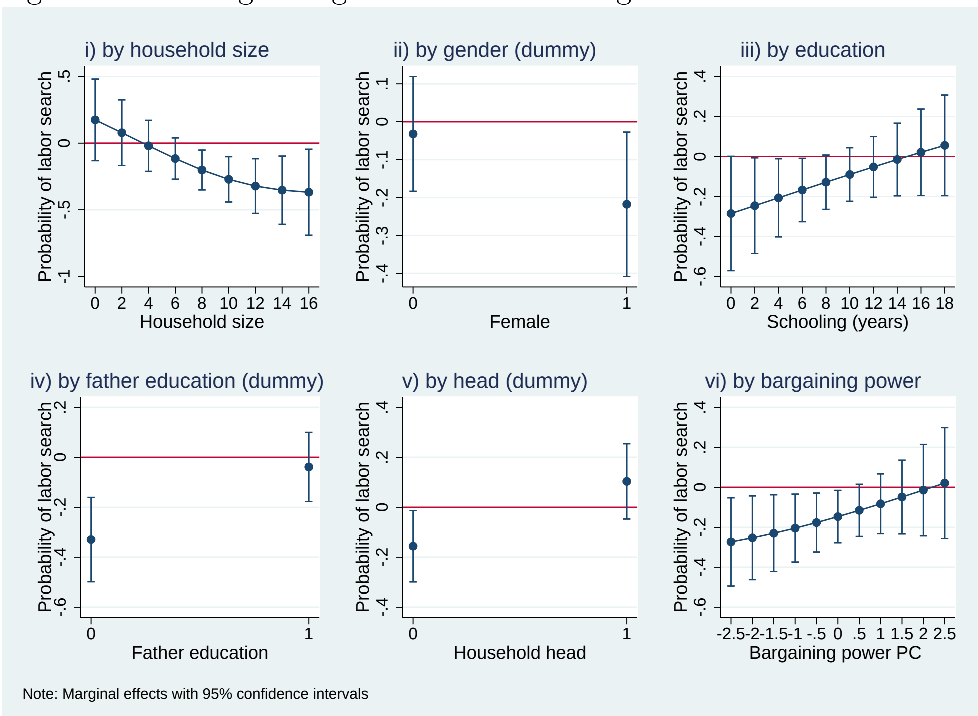


Figure A5: Average marginal effects of Having heard about MF