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MICROFINANCE AND POVERTY REDUCTION: EVIDENCE FROM DJIBOUTI

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Abstract:

Does access to microfinance improve household welfare?

We seek the answer to this question using data on 2,060 borrower and non-borrower households based in six major urban centers of Djibouti. We construct a composite index of multi-dimensional poverty and carry out estimations using a number of econometric techniques. Our results show that neither access to micro-credit nor its ostensibly productive use is significantly associated with poverty regardless of the duration of time since the loan was acquired. This holds both for access to, and the amount of micro-credit obtained. The results raise doubts on the effectiveness of Djibouti's microfinance programme.

Keywords: Microfinance, poverty, productive loans, Djibouti.

1. Introduction :

Extreme poverty is endemic to the countries located in the Horn of Africa. With limited natural resources, a poorly developed industry and climatic conditions unfavourable to agriculture, Djibouti has experienced economic crises since the 1990s. The country was forced to conclude agreements with the International Monetary Fund (IMF) in 1996 and the World Bank in 1997. The deterioration of the Djiboutian economy was due, not only to domestic issues (proliferation of internal conflicts) but also to external difficulties (decline in development aid, increased regional competition from the port of Assab[1], influx of refugees from Somalia and Ethiopia). Between 1992 and 1996, the economic situation deteriorated sharply, and the GDP declined[2] (Foch,2010). Since 2010 however, the economic growth rate has increased substantially from 3.5% in 2010 to 7% in 2018. This strong growth fuelled by investments in trade infrastructure has enabled the country to rank among the fastest growing economies in the region (World Bank, 2018).

Thanks to a strong government focus on poverty alleviation, Djibouti has been able to reduce extreme poverty from 42.2% to 21.3% between 2002 and 2017 (DISED, 2018). A major social safety net has been set up to combat poverty.

The concept of microfinance has also been adopted as a vital tool to improve the socio-economic conditions of those segments of the population excluded from the traditional banking system. After some initial steps taken in the 1990s, the microfinance sector gained visibility in the country during the 2000s with the establishment of Social Fund for Development (FSD), the Djiboutian Social Development Agency (ADDS) and an authority managing micro-loans through Credit Unions (*Caisse Populaire d'Epargne et de Crédit)*. By 2016, one-third of Djibouti's households had access to microcredit mainly provided by one of the three principal microfinance institutions (MFI's). In all, these institutions provided a total of US$12.3 million in loans. Despite this impressive growth of microfinance, there is little evidence so far to show its effectiveness or its contribution to poverty reduction in Djibouti.

Microfinance is seen by some as a 'magic wand' against poverty, a means to solve all problems. However, evidence on the effectiveness of microfinance as a poverty reduction measure in developing countries is mixed. At one end of the spectrum, there are studies affirming that microfinance is a positive and effective mechanism (for example Mosley, 2001; Imai and al.; 2010; Imai and Azam, 2012; Akotey and Adjasi (2016)). In contrast, some studies argue that microfinance actually plunges the population further into poverty, affecting women in particular (for example, Coleman, 1999; 2006; Crepon and al, 2015; Seng, 2017). Others have warned against considering microfinance as a miracle solution, claiming that it helps poor households only to a limited extent, and have advocated its use with 'cautious optimism' (Banerjee and al., 2009; Karlan and Zinman, 2009; Duvendack and Palmer Jones, 2012). The divergent conclusions

[1] The truce signed in 1993 between Eritrea and Ethiopia, which allowed Ethiopia to access the sea via the port of Assab, severely affected the country's economic situation.

[2] The country's GDP growth rate was -3.9% in 1993, -2.9% in1994 and -3.1% in 1995.

drawn from existing literature are possibly a reflection of the diverse contexts of the studies as they focus on different geographical areas and use different methodologies.

In this study we analyse the welfare aspects of microfinance in Djibouti, a country which has received little interest upto now. The significance of the country in this context lies not only in the relatively high penetration of micro-finance institutions but also in the high vulnerability of the country's population to climatic changes and geo-political uncertainty.

We employ a large household survey conducted in 2015 by the Department of Statistics and Demographic Studies (DISED) in the capital, Djibouti-city, and the five regional capitals to analyse whether the households which take micro-loans manage to come out of poverty, does this depend on the amount of loan acquired or the time since it was obtained. We construct a composite poverty index by combining household characteristics pertaining to agriculture, employment, livestock, transport, household assets and sanitation. We employ Probit and Tobit models to estimate the effect of microfinance on the household's wealth status, and control for potential selection bias with inverse probability weighting (IPW) and augmented inverse probability weighting (AIPW). We find that the evidence supporting beneficial effects of microfinance services in Djibouti so far is not robust.

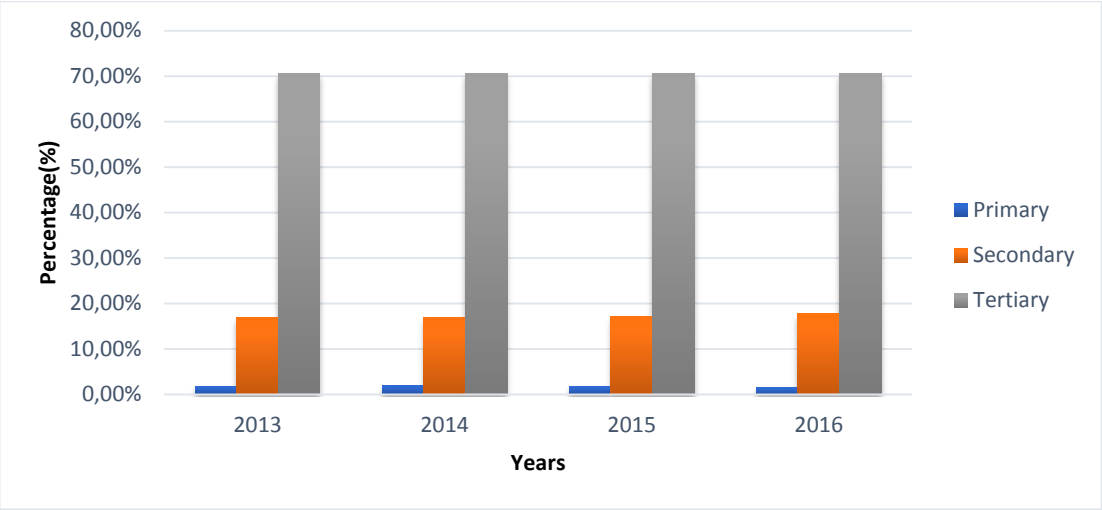
The following section of the document summarizes the microfinance sector and the profile of poverty and vulnerability in Djibouti. Section 3 presents the data and methodology used. Results are presented and discussed in Section 4. Robustness measures are described in Section 5. The final section concludes and offers policy recommendations.

2. Microfinance and poverty in Djibouti- an overview.

2.1. State of poverty in Djibouti.

Djibouti is considered a low-income country, ranked 172 out of 188 countries on the development index. More than 70% of the country's population lives in urban areas. Economic activity is dominated by the public and tertiary sectors, which contribute 70.5% of GDP, much of which is concentrated in the capital (Djibouti-city). The contribution of the primary sector (1.8% of GDP) remains marginal, due to unfavourable climate, limited water resources, poor agricultural and fishing potential. The secondary sector contributes 16.9% of GDP, lagging behind the tertiary sector and limited due to the unavailability of primary materials, high production costs and labour shortage (Figure 1).

Figure 1: Sectoral contributions to GDP (in %).



Source: Djibouti Economic Model Report (Ministry of Economy and Finance, 2015).

According to EDAM-IS (DISED, 2017), extreme poverty for the country as a whole is estimated at 21.3% (Table 1). There seems to be a persistent gap between the well-being of inhabitants in the capital, Djibouti-city and those in other regions (Table 1). The extreme poverty rate is estimated at 13.6% in Djibouti-city compared with 45.0% in the other regions. Overall, 35.8% of the population is unable to meet its daily needs, whether food or non-food. The Gini index of the country at 0.42 is among the highest in the Middle-East and North Africa (MENA) region.

Insert Table 1 here

2.2. Djibouti's microfinance sector

Microfinance emerged in Djibouti in 2008. In 2010 it extended into rural areas. The main objective was to offer financial services to poor households, thereby enabling them to become self-sufficient by setting up income-generating activities.

There are three main microfinance actors :

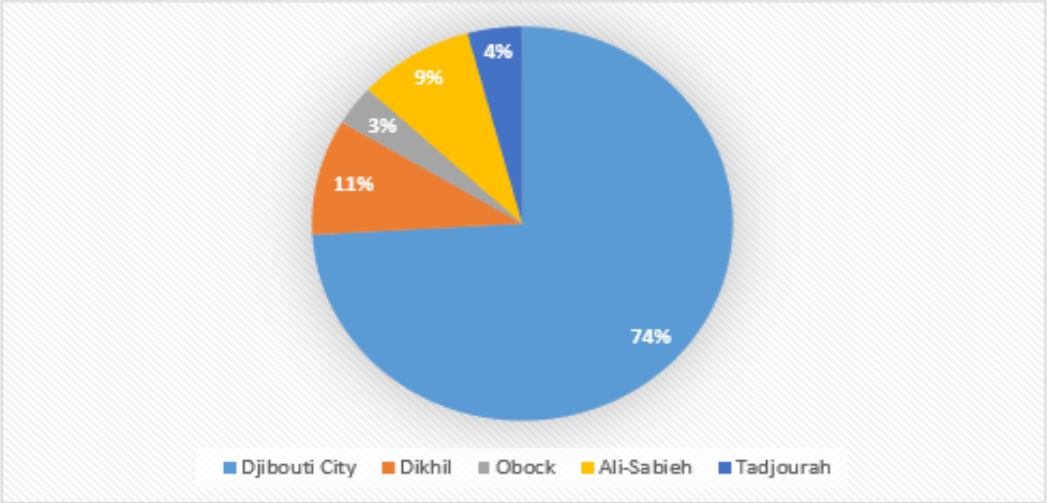
The first actor is the Djiboutian Social Development Agency (ADDS). Its role is to structure and institutionalize microfinance activities as well as providing financial and logistic support, through donors and partners, for the development of the sector in question. The second actor is the bank. The relations between commercial banks and microfinance actors are limited to current operations (e.g. deposits, withdrawals and transfers). However, commercial banks do not provide credit lines for microfinance

activities, nor do they cover refinancing. The last actor is the public authority, which has established a legal and regulatory framework for the further development of the sector. In addition, the state has taken the initiative of setting up a national microfinance reflection committee under the supervision of the central bank.

At the national level, the microfinance sector is served by three major Credit Unions (*Caisse Populaire d'Epargne et de Crédit),* the CPECs. The first CPEC is in Djibouti city, the second in the southern region, based in Ali-Sabieh and the third in the northern region based in Tadjourah. These CPECs are incorporated as savings and credit cooperatives.

In terms of distribution, the CPEC of Djibouti comes on top with 18022 members for which loans worth 1,619 million Djiboutian Francs (FD), about 74% of the total, have been disbursed (Figure 2). The CPEC of Dikhil comes in second place with 1583 members in all categories, allocating an amount of 208 million FD (9 % of the total). The CPEC of Ali-Sabieh has 104 members with a micro-credit grant of 194 million FD (10 % of the total) of microcredit granted. The smaller CPECs of the North, notably those of Tadjourah and Obock, have 1,063 and 1,291 members respectively, and account for 91 million FD (4 % of the total) and 72 million FD (3 % of the total) in dispersed loans.

Figure 2: Share of credit granted by region (in %).



Source : Djibouti Social Development Agency (ADDS, 2015).

3. Data and Methodology

3.1. Data

Our analysis is based on the survey of the 2015 Djibouti Urban Poverty Reduction Project (PREPUD). This survey, conducted by the Djiboutian Agency for Development (ADDS) and the Department of Statistics and Demographic Studies (DISED) covers the capital, Djibouti city and the five regional capitals, Arta, Ali-Sabieh, Dikhil, Obock et Tadjourah. The questionnaire was in French and aimed at determining the impact of the microfinance project on the living conditions of households receiving loans. The idea was to ascertain to what extent microfinance has contributed, through the provision of credit, to the well-being of borrowers. The five main cities of the regions cover 30% of the total population. The survey covered a total of 2060 households.

3.2. Model and Variable Description

The central hypothesis of our study is that access to microfinance is associated with lower poverty. Since the data available is cross-sectional in nature, a comparison can be made between households that have benefitted from MFIs loans and those that have not. A positive effect of access to microfinance can be statistically obtained provided there are more recipients among poor households of contracted loans from microfinance institutions (CPECs) than non-recipients.

Our empirical model can be given as:

$$Pov_i = \beta X_i + \alpha MF_i + \varepsilon_i \qquad (1)$$

Where Pov_i is the poverty indicator, X_i measures the matrix of control variables for i households, MF_i is the variable of interest, i.e. access to microfinance. β and α represent the coefficients of the controls and the variables of interest respectively. Finally, ε_i is the error term that follows normal distribution.

Dependent variable

We construct a composite poverty indicator that captures various aspects of well-being such as agriculture, employment, livestock, transport, household assets and sanitation. The constituent indicators of the index are listed in Table A1 in the Appendix. The composite poverty index of Katsushi et al (2010) took into account, in addition to the various dimensions mentioned above, the dimensions of income and food security. In our study, however, we could not include these two dimensions due to the limitations of the survey design.

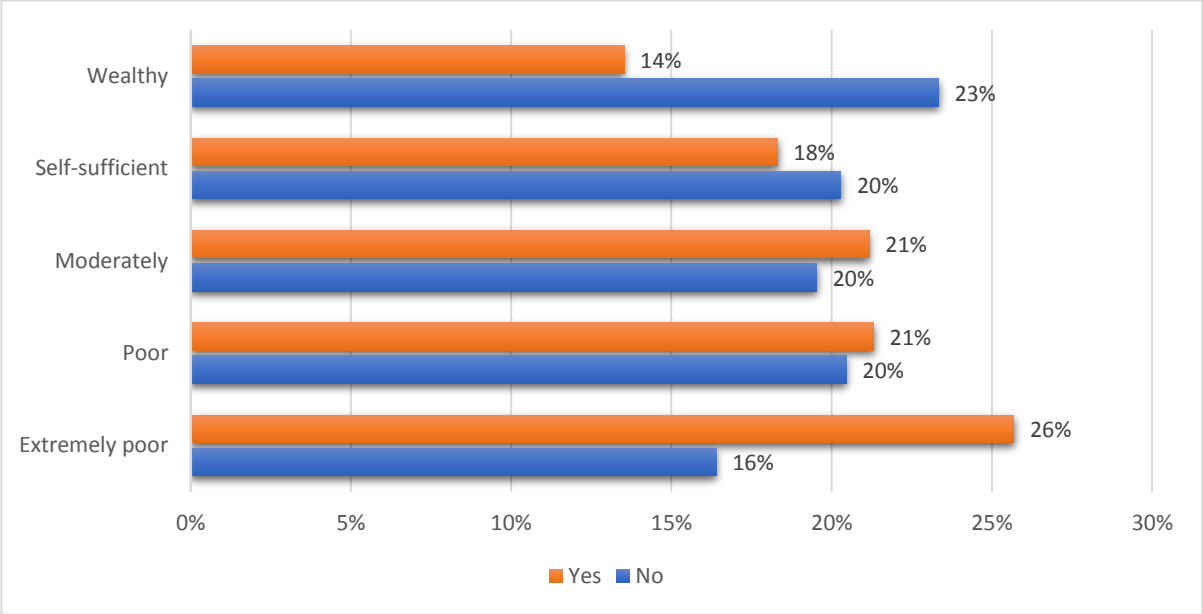
Households are grouped into five wealth categories, namely :(i) extremely poor, (ii) poor, (iii) moderately poor (iv) self-sufficient and (v) wealthy.

Households from the extremely poor, poor and moderately poor categories experience deteriorating housing situations. In addition, they live in dwellings that do not benefit from sanitary facilities with widespread overcrowding and cramped space. The main energy sources are solar panels and candles. Poor and moderately poor households own large quantities of livestock (camels, cattle and sheep). The principal means of transport used by these categories are mopeds and public transport (buses and others) while many travel on foot.

Self-sufficient and wealthy households have certain assets in common, such as access to electricity, water source used, fuel used in the kitchen, flooring material and the type of toilet. They diverge, however, in terms of waste water disposal and household size.

In terms of access to microfinance, 26% of households belong to the extremely poor category, 21% come from poor and moderately poor categories, whereas 18% and 14% of the households come from the self-sufficient and wealthy categories respectively (Figure 2).

Figure 3: Access to microfinance by household wealth status.



Source: Author's calculations using PREPUD 2015.

24% of extremely poor households who received microcredits were able to use them for productive purposes, while 21%, 22%, 18% and 15% of households from poor, moderately poor, self-sufficient and wealthy categories were able to use their loans for the purpose of starting income-generating activities.

Variables of Interest

We use two indicators of access to microfinance:

(a) a binary variable indicating whether the household is a client of a microfinance institution or not and (b) a binary variable indicating whether a household took out credit for productive purposes or not.

(b) «Being a client » means that all household members had a savings account or an account with MFIs at the time of the survey.

The definition of "productive purposes" is based solely on the respondents own reported use of the loan.

Approximately 62% of borrowing households use microcredit offered by formal financial institutions (CPECs of Djibouti, the North the South), while the remaining 38% subscribe to microcredit from informal lenders (friends, traders, employers and others).

64% of borrowing households report that they use credit for productive activities, while 36% reported using their loans for non-productive activities (Table 2).

Insert Table 2 here

Control variables

The control variables used in our econometric analysis relate to the socio-demographic characteristics of the household: age of household head, sex of household head, marital status, level of education, geographical regions, household size and dependency ratio.

34% of female-headed households acquired microcredit and 74% of married households took out loans from microfinance institutions. On average, households which took micro-loans have received more education: 36% of household heads granted credit have attained primary education, 53% have attained secondary level, while 11% reached a higher level. 25% of households benefitting from microcredit come from Djibouti city while the majority (75%) are from the interior regions, i.e the five regional capitals, Ali-Sabieh, Arta, Dikhil, Obock and Tadjourah.

3.3. Methodology

The empirical analysis is carried out as follows :

First, we use the Probit model to estimate the effect of access to microfinance and productive loans on poverty reduction. Next, we use the Tobit model to study the effects on poverty of the amount (in logarithm) of microcredit and the amount (in logarithm) of loans acquired for productive purposes.

In the third step, two techniques, inverse probability weighting (IPW) and augmented inverse probability weighting (AIPW) were used to take into account the possibility that households with access to credit may differ in observable characteristics from those without access to credit, thus causing selection bias. In addition, a wide range of robustness measures were carried out by estimating alternative specifications and models using different population sub-samples.

4. Results

Table 3 presents bivariate statistics for access to microcredit. We see that borrower and non-borrower households differ little in most of the economic, demographic and geographical features. The borrower households on average have a higher dependency ratio, suggesting a greater need for the working-age members to engage in income-generating activities.

The association between access to microcredit and poverty estimated through probit model (shown in Table 4) however, appears to be statistically significant at the 1% level. The marginal effects shown at the bottom of Column 1 show that a household having taken loan from an MFI is 8.5% less likely to be extremely poor compared with a non-borrowing household, keeping all other factors constant. In contrast, the relationship between acquiring a loan for productive purposes and extreme poverty is not found to be significant (Column 2).

Is the microcredit – household wealth relationship suggested above specific to a wealth category? Focusing on the moderately poor, self-sufficient and wealthy household categories, we find the association between household wealth and the incidence of acquiring a micro-loan to be insignificant (P-value=0.39; P-value=0.22 and p-value=0.45 respectively).The results for acquisition of productive loans are likewise insignificant.

Insert Table 3 here

Insert Table 4 here

Next we check if the household wealth status is associated in any way with the amount of micro-credit the household obtains. Table 5 presents results for Tobit estimations for the relationship between the

amount of loan and the incidence of poverty. The relationship is found to be insignificant (Column 1). Likewise, the association between poverty and amount of productive loans acquired (Column 2) is found to be statistically insignificant (P-value = 0.283).

Insert Tables 5 & 6 here

The lack of statistical significance of the poverty – microcredit relationship seen so far could be lined with the length of time since the loan was obtained. We explore this possibility by considering sub-samples of beneficiaries who acquired loans less than or more than six months before the time of the survey. Results given in Table 6 suggest that time is not a significant factor as the relationship is found to be insignificant for both subgroups of beneficiaries.

5. Robustness measures

5.1. Matching estimations

It is possible that households who participate in the microfinance programme differ from those who do not. For instance, as mentioned above, the heads of borrowing households are on average more educated than those of non-borrowing households. We account for this potential selection bias by using two matching methods, namely Inverse Probability Weighting (IPW) and Augmented Inverse Probability Weighting (AIPW).

IPW improves over Propensity Score Matching (PSM) by allocating higher weightage to observations receiving an unlikely treatment. This reweighting allows higher weights to be assigned to individuals in the middle of the probability distribution and lower weights to the extremes (Wooldridge,2007). The second technique is the Weighted Augmented Inverse Probability estimator (AIPW), a 'doubly robust' method, with the properties of both the regression-based estimator and the IPW estimator, requiring either the propensity or outcome model to be correctly specified (Cao et al., 2009).

Table 7 presents the IPW and AIPW estimates. The results of the two estimators are statistically and qualitatively similar. For both techniques, the results of access to microfinance are statistically insignificant as P-value=0.228 is above the 10% level. The results of access to productive loans too follow the same direction as previous results.

Insert Table 7 here

5.2. Multiple Hypotheses Testing

We conduct the Multi-Variance and Covariance tests (MANOVA) using the composite poverty indicator focusing on poor households. The results of the four statistics (Wilks' Lambda, Trace de Pillai, Laweley-Hotelling and Roy) reported in Tables 8 and 9 show that the null hypothesis of equality of means for access to microcredit is statistically insignificant at the 10% level (P-value=0.513). The result of the test for access to productive loans is similar (P-value=0.718 > 0.10).

We also use the Bonferroni correction to test the statistical significance of the regression coefficients of our variables of interest. The method corrects the p-value in the case where several tests are performed simultaneously on the same data. The corrected coeficients remain insignificant as before (P-value = 0.513 for the access to loan model and 0.718 for the access to loans for productive purposes model).

Insert Table 8 & 9 here

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6. Concluding remarks

In this study, we aimed at finding whether access to microfinance is associated with lower incidence of poverty. We used a household survey on the use of microfinance services carried out in 2015 in the major urban centers of Djibouti to seek answer to this question. We constructed a composite indicator for wealth status of the household and employed a number of empirical strategies.

We failed to find a robust association between microfinance loans obtained by Djiboutian households and their wealth status. Whether or not the household acquired a micro-credit, and whether it reported using the loan for productive purposes shows no significant association with its being poor. This is also true for the amount of loan the household obtained. The results are robust across specifications and econometric techniques employed. The lack of significant beneficial effect of microfinance found in the study adds to the growing literature questioning the effectiveness of microfinance as a tool for poverty alleviation.

The findings raise a number of questions for the policymakers:

What are the causes for this lack of positive impact? Is it due to the relatively short span of time since the programme had been launched ? To what extent does it result from the cost of borrowing ? The fact that the majority of the beneficiaries of microcredit disbursed does not come from the poorest segments of the society points in this direction. A better targeting of loan disbursement can therefore enhance the effectiveness of the programme but would require better training and awareness of the MFI staff on the ground.

Another possible implication of the study's findings is the need to extend the focus on income-generating activities. Sectors such as fishing and agriculture which create employment and lead to rapid increase in household income should be given preference.

Finally, the impact of microfinance on Djiboutian households could be enhanced by focusing on the skill development of the population. Higher financial literacy, better technical knowhow and professional skills can enable the poor to make good use of available opportunities with the help of small loans.

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Appendix

Table 1 : Poverty and inequality indicators in Djibouti 2017

Indicator	National	Djibouti-city	Other regions	Urban area	Rural area
Extreme Poverty	21.1%	13.6%	45.0%	14.8%	62.6%
Poverty gap	71%	35%	18.6%	5.2%	26.4%
Severity of poverty	34%	13%	10.1%	26%	14.4%
Overall poverty	35.8%	28.2%	59.8%	27.6%	78.4%
Gini (coefficient)	0.42				
D9/D10	6.60				

Source: DISED (2018).

Table A1: Dimensions and indicators used to construct the composite poverty index.

Dimension	Indicators
Agriculture	Ownership of agricultural land
Employment	Types of work
Livestock	Camels, cattle, sheep and poultry
Transportation	Car ownership /modes of transport used
Property and type of accommodation	Types of housing, housing tenure status, roofing materials and exterior wall construction.
Household assets	Ownership of refrigerator, telephone (fixed and mobile), computer and television.
Sanitation	Sources of water and energy, household waste and waste-water disposal.

Table 2: Data Description

Variables	Definition	Proportion/Mean
Dependent		
IBR	A composite indicator that captures various aspects of wellbeing including agriculture, livestock, access to basic needs and quality of the house/accomodation, assets of the household and sanitation facilities.	0.19 0.20 0.20 0.19 0.19
IBR	Dummy variable takes 1 if head is poor, 0 otherwise	0.20 0.80
Demographic variable		
Age of household head	Age of household head (in years)	49.51
Age square of household head	Age squared of household head (in years)	
Sex of household head	1 the household is a female, 0 otherwise	0.34
Marital status	1 if the household head is married, 0 otherwise	0.74
Education	Categorical form, if household head has primary level or less, 2.secondary level and 3. higher education.	0.36 0.53 0.11
Region	Categorical form, if the household head lives in: 1. Djibouti, 2. Ali-Sabieh, 3. Dikhil, 4. Obock, 5. Tadjourah and 6. Arta.	 0.16 0.25 0.16 0.16 0.13 0.14
Region	Dummy variable takes 1 if head lives in Djibouti, 0 otherwise	0.25 0.75
Household size	Number of household members	1.81
Dependency ratio	Dependency ratio (ratio of household members under age of 15 years or over 60 years to total members).	16.17
Interest variable		
Loan access	1 - if the household has outsanding loans for the last years and 0 otherwise.	0.62 0.38
Numbers of loans	Number of loans taken out by the households for the last year	2.79
Loan amount	Total amount of outstanding loan for the last/previous year.	227 894
Productive loan access	1 if the household has access to productive outstanding loans for the last years and 0 otherwise.	0.64 0.36
Productive loan amount	Total amount of productive outstanding loans for the last year.	214 427

Source: Authors' calculations using PREPUD 2015.

Table 3: Household characteristics by access to microfinance

Variables	Without access to microfinance		With access to microfinance		Difference
	Mean/Proportion	SE	Mean/Proportion	SE	lnMean
Dependent variable	3.141	(0.039)	2.744	(0.049)	2.989
IBR (ref: poor)					
Household characteristics					
Age of household head	49.007	(0.497)	50.337	(0.620)	49.513**
Sex of HH (ref = female)	0.695	(0.013)	0.614	(0.017)	0.664
Marital status (ref = married)	1.149	(0.013)	1.125	(0.018)	1.140
Education level of household head	1.756	(0.027)	1.757	(0.039)	1.756
Région (ref : Djibouti)					
Ali-Sabieh	0.165	(0.010)	0.147	(0.013)	0.158
Arta	0.142	(0.009)	0.105	(0.011)	0.128
Dikhil	0.155	(0.010)	0.164	(0.013)	0.158
Obock	0.153	(0.010)	0.173	(0.014)	0.160
Tadjourah	0.228	(0.012)	0.294	(0.016)	0.253***
Dependency ratio	16.755	(0.194)	15.204	(0.296)	16.166***
Household size	1.819	(0.019)	1.797	(0.026)	1.811

Source: Authors' calculations

Notes: Standard errors given in parentheses. *** p< 0.01; **p<0.05; *p<0.1

Table 4 : Micro-credits and households wealth-Probit estimation

	Extreme poverty				Wealth category (Moderately Poor)			
	Access to microfinance		Access to productive loan		Access to microfinance		Access to productive loan	
Explanatory variables	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Interest variable								
Access to microfinance	0.363***	(0.117)	-0.111	(0.288)	-0.196	(0.335)	-0.148	(0.335)
Household characteristics								
Age of household head	0.027	(0.017)	0.034	(0.022)	-0.033*	(0.034)	-0.038	(0.035)
Age square of HH	-0,002	(0.000)	-0.000	(0.000)	0.000*	(0.000)	0.000	(0.000)
Sex of HH (ref = female)	-0,08	(0.152)	-0.106	(0.274)	0.283	(0.205)	0.275	(0.363)
Marital status of HH	-0,109	(0.105)	-0.014	(0.130)	0.282*	(0.423)	-0.159	(0.205)
Education level of HH								
Less and primary	-0,019	(0.223)	0.234	(0.322)	0.486**	(0.423)	0.596	(0.423)
Secondary and more	0,273	(0.219)	0.570	(0.326)	0.150	(0.338)	0.184	(0.337)
Region (ref:Djiboouti)								
Ali-Sabieh	-0.177	(0.287)	-0.091	(0.342)	-0.019	(0.398)	-0.248	(0.398)
Dikhil	0.035	(0.265)	-0.531	(0.402)	-0.744***	(0.413)	0.519	(0 .413)
Obock	-0.338	(0.216)	-0.162	(0.341)	0.706	(0.239)	-1.005***	(0.239)
Tadjourah	-0.122	(0.215)	0.005	(0.304)	-0.204	(0.252)	-0.449**	(0.252)
Household demography								
% dependency ratio	-0.004	(0.007)	0.007	(0.009)	-0.009	(0.017)	-0.009	(0.017)
household size	-0.116	(0.073)	-0.179	(0.108)	-0.116	(0.124)	0.042	(0.124)
Marginal effect	0.085***	(0.018)						
Constant	-1.165***	(0.446)	-1.245**	(1.245)	-1.069**	(0.917)	-0.340	(0.917)
Number of observations	794	796	276	276	794	794	276	276

Source: Authors' calculations

Notes: Standard errors given in parentheses. *** p< 0.01; **p<0.05; *p<0.1

Table 5: Result of tobit model main covariate: totals of amounts and productive loans.

Explanatory variables	Poverty (IBR=Poor)			
	Logarithm total of amount loan		Logarithm Amount of productive loan	
	Coef	SE	Coef	SE
Interest variable				
Logarithm of amounts loans	0.161***	(0.080)	-0.137	(0.125)
Household characteristics				
Age of household	0.019	(0.029)	-0.020	(0.063)
Age square of household head	-0.000	(0.000)	0.000	(0.001)
Sex of HH (ref = female)	0.034	(0.229)	-0.207	(0.319)
Marital status of HH (ref = married)	-0.164	(0.231)	-0.537*	(0.291)
Education level of HH (ref = none)				
Less and Primary	-0.590**	(0.279)	-0.740	(0.549)
Secondary and more	-0.527**	(0.222)	-1.330**	(0.523)
Region (ref : Djibouti)				
Ali-Sabieh	-0.102	(0.408)	1.085*	
Arta	0.122	(0.419)	1.538**	(0.551)
Dikhil	0.568	(0.392)	1.285**	(0.684)
Obock	0.055	(0.366)	0.504	(0.582)
Tadjourah	0.227	(0.379)	0.852	(0.569)
Household demography				(0.642)
% dependency ratio	-0.008	(0.015)	-0.042**	(0.197)
Household size	0.195	(0.121)	-0.046	(0.185)
Marginal effects	0.046***	(0.015)		
Constant	-2.734**	(1.297)	3.106	(2.500)
Number of observations	274	274	96	96

Source: Authors' calculations

Notes: Standard errors given in parentheses. *** p< 0.01; **p<0.05; *p<0.1

Table 6: Effect of participation in the programme on poverty – Probit estimation

	D1 (Participation less than 6 months)		D2 (Participation more than 6 months)	
Explanatory variables	Coef	SE	Coef	SE
Interest variable				
Period of participation	-0.208	(0.205)	0.208	(0.205)
Household characteristics				
Age of household	0.016	(0.027)	0.016	(0.027)
Age square of household head	-0.000	(0.000)	-0.000	(0.000)
Sex of HH (ref = female)	-0.001	(0.205)	-0.001	(0.205)
Marital status of HH (ref = married)	-0.143	(0.190)	-0.014	(0.190)
Education level of HH (ref = none)				
Less and Primary	-0.553	(0.302) **	-0.553	(0.302) **
Secondary and more	-0.530	(0.228) **	0.530	(0.228) **
Region (ref : Djibouti)				
Ali-Sabieh	-0.029	(0.334)	-0.029	(0.334)
Arta	0.164	(0.362)	0.164	(0.362)
Dikhil	0.549	(0.354)	0.549	(0.353)
Obock	0.075	(0.326)	0.075	(0.326)
Tadjourah	0.342	(0.306)	0.342	(0.306)
Household demography				
% dependency ratio	-0.007	(0.014)	-0.007	(0.014)
Household size	0.141	(0.097)	0.141	(0.097)
Constant	-0.616	(0.755)	-0.824	(0.854)
Number of observations	274	274	274	274

Source: Authors' calculations

Notes: Standard errors given in parentheses. *** p< 0.01; **p<0.05; *p<0.1

Table 7: Microfinance and poverty reduction-IPW and AIPW estimates

Inverse-Probability Weight	**Access to microfinance**		**POmean**		**Access to productive loan**		**POmean**	
	Withaccess	**Withoutaccess**	**Withaccess**	**Withoutaccess**	**With productive loan**	**Without productive loan**	**With productive loan**	**Without productive loan**
ATE	-0.029	-0.021	0.232***	0.228***	-0.225	-0.225	0.429***	0.429***
	(0.036)	(0.039)	(0.031)	(0.034)	(0.094)	(0.094)	(0.076)	(0.076)
ATET	-0.024	-0.024	0.237***	0.237***	-0.225	-0.225	0.429***	0.429***
	(0.048)	(0.048)	(0.044)	(0.044)	(0.094)	(0.094)	(0.076)	(0.076)
Observations	780	780	780	780	96	96	96	96
Augmented IPW								
ATE	-0.024	-0.024	0.231***	0.231***	-0.223	-0.223	0.428***	0.428
	(0.042)	(0.042)	(0.038)	(0.038)	(0.094)	(0.094)	(0.076)	(0.076)
Observations	780	780	780	780	96	96	96	96

Source: Authors' calculations

Notes: Standard errors given in parentheses. *** p< 0.01; **p<0.05; *p<0.1

Table 8: Multivariate analysis of variance and covariance- Access to microfinance

Source	Statistic		df	F (df1, df2)		F	Prob>F
Access to microfinance	W	0.9998	1	1.0	1.0	0.43	0.5130e
	P	0.0002		1.0	2041.0	0.43	0.5130e
	L	0.0002		1.0	2041.0	0.43	0.5130e
	R	0.0002		1.0	2041.0	0.43	0.5130e
Residual		2041					
Total		2042					

Source : Authors' calculations

W = Wilks' lambda, L = Lawley-Hotelling trace, P = Pillai's trace R = Roy's largest root

e = exact, a = approximate, u = upper bound on F

Table 9: Multivariate analysis of variance and covariance-Access to productive loans

Source	Statistic		df	F (df1, df2)		F	Prob>F
Access to productive loan	W	0.998	1	1.0	778.0	0.13	0.718e
	P	0.0002		1.0	778.0	0.13	0.718e
	L	0.0002		1.0	778.0	0.13	0.718e
	R	0.0002		1.0	778.0	0.13	0.718e
Residual		778					
Total		779					

Source: Authors' calculations

W = Wilks' lambda, L = Lawley-Hotelling trace, P = Pillai's trace R = Roy's largest root

e = exact, a = approximate, u = upper bound on F