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Impact of Microcredit on Poverty: Evidence from Ghana

Aristide Bonsdaounde Valea[1, 2] , Aminata Diagne[1, 2] and Audon Honvoh[1]

[1]*Department of Agri-Food Economics and Consumer Science, Laval University*
[2]*Centre for Economics Research on the Environment, Agri-food, Transportation, and Energy (CREATE)*

Abstract

Microcredit is a specific means of fighting poverty in developing countries. Given the contrasts in its impact on poverty raised in the literature, evaluations with more rigorous methods are needed. This paper assesses access to microcredit impact on poverty through data from Ghana collected in 2004. The propensity scores matching method concludes that access to microfnance has a positive impact on household relative poverty index in the whole sample. Otherwise, this impact differs by place of residence. Indeed, while microcredit impacts positively poverty index in urban area, it has no impact in rural area. The quantile regression method has also been used to evaluate microcredit access on poverty distribution. The results show microcredit increase second and third quartile meaning microcredit is more beneficial for the richest household than the poorest. This result corroborates the schism hypothesis of microfnance denounced in the literature.

Keywords: **Microcredit, Poverty, Microfnance, Ghana, Impact evaluation, Quantile regression**

1 Introduction

Perceived as an adequate tool for poverty reduction, microfinance has been used by several countries and organizations to provide financial services to populations with little or no access to classical financial systems including banks (Stewart et al., 2010). First of all, at the social level, it stands out from banks through the financing of income-generating activities of poor households (Morduch et al., 1998). Second, from the financial perspective, it has made it possible to grant small loans called "Microcredits to low-income people" with solvency deemed insufficient by the traditional financial institutions (Stewart et al., 2010). These loans enable them to create or develop microenterprises or income-generating activities (Morduch, 2000; Servet, 2009).

Although microfinance is recognized as a powerful tool in the fight against poverty in developing countries, its positive impact on poverty reduction is not unanimous in the scientific literature. The 2012 report presented at the Microcredit Summit also highlighted the controversy surrounding the role of microcredit in poverty reduction and key microcredit stakeholders (Maes and Reed, 2012).

Generally, there are two main positions in the literature on microfinance and poverty reduction. First, the proponents of the positive impact of microfinance on poverty consider that access to financial resources through the traditional financial system in the developing countries is very limited for the poor. Therefore microfinance appears to be a source of financing for activities economic conditions. In addition to providing financial products adapted to the needs of the poor, loan guarantees are less demanding than conventional bank loans (Ferdousi, 2015). Some authors consider that microfinance guarantees access to basic social services such as education and health in environments where social protection is not well developed (De-Loach and Lamanna, 2011). These theoretical perceptions have been corroborated by several studies that demonstrate the empirical evidence of the positive impact of microfinance on poverty reduction. Using a sample of seven countries including Bangladesh, Bolivia, India, Indonesia, Kenya, Malawi and Sri Lanka, Hulme and Mosley (1996) show through the control group approach that microcredit has a positive impact on household living conditions in that 91% of poor borrowers had an increase in their income and, above all, the effect was higher (more than 50%) for poor and vulnerable households. Khandker (2005), used a panel sample of 1,688 poor households in Bangladesh and a dynamic model and concludes that microcredit has a positive impact on the living conditions of poor households, especially for women, through an increase of consumption spending. These results are corroborated by Adjei et al. (2009), Berhane and Gardebroek (2011), Khan (2014), Miled and Rejeb (2015), Bangoura and Hounwanou (2015). Khan (2014) was particularly interested in the impact of microcredit programs in Pakistan on formal, semi-formal and informal channels. The results indicate that microcredit has improved the economic situation of beneficiary regions at the global level by reducing poverty through smoother consumption, better population risk management, gradual asset building, microenterprise development, improvement of income-earning capabilities and quality of life.

By focusing on the impact of microcredit by place of residence, Imai et al. (2010) show through an empirical study in India that access to microfinance has a more significant positive impact in rural areas than in urban areas. This study is particularly interesting because it integrates the problems of endogeneity and selection bias using two different methods including that of Propensity Score Matching and Treatment Effect. These methods lead to the same conclusion, reflecting the robustness of the results.

Second, several authors consider the impact of microfinance on poverty to be moderate. Contrary to what is often observed, the loans granted to beneficiaries can lead them to situations of over-indebtedness. Using the randomization technique on a sample of 1,148 poor women from 40 villages in Mongolia and the method of instrumental variables, Attanasio et al. (2015) show that unlike the group lending program which has a positive impact on female entrepreneurship and household food consumption, the individual lending program (microcredit) has had no impact on poverty.

Weiss and Montgomery (2005) results have shown that access to microcredit in Asia certainly reduces poverty, but does not necessarily impact all categories of the poor. Indeed, individuals belonging to the chronic poor category do not have their conditions improving through microcredit. Compared to the transitional poor, the chronic poor of the Asian continent borrow money for survival or protection because of the low and irregular nature of their income. This means that microcredit cannot often generate a return on investment, especially since the investment is unproductive.

In a study comparing the poverty level of a sample of 588 clients of five microfinance institutions with the poverty level of the population of La Paz in Bolivia, Navajas et al. (2000) show that the microcredit granted by these institutions does not affect the poor, but those who are either just above or just below the poverty line. These results were also confirmed by Amin et al. (2003), who assess the impact of microcredit programs on the relatively poor and vulnerable populations in two Bangladeshi villages. Using a panel data set with monthly consumption and income observations for 229 households, the authors conclude that microcredit has been successful in reaching the poor but is less effective in changing the living conditions of vulnerable households. Moreover, these authors go so far as to show that households that are both poor and vulnerable are not affected by the microfinance institutions' intervention in the poorest village.

Augsburg et al. (2015), use the randomized controlled trial technique for a total of 995 households in Bosnia and Herzegovina and show that microcredit supposedly helped the poorest, just contributed to increase profits for microfinance institutions while reducing the consumption and saving of the poorest households. These results were also confirmed by Banerjee et al. (2015) for the microcredit program in India, Crépon et al. (2015) for Morocco, Angelucci et al. (2015) for Mexico. All these studies show that microcredit has no impact on the poorest households incomes, and that it only contributes to raising the standard of living of the richest.

A study by Stewart et al. (2010) in ten sub-Saharan African countries shows that poor households are made poorer by microfinance, namely microcredit, which contributes to rich households. This study used a review of 15 studies, including four randomized controlled trials, two non-randomized controlled trials and nine control group studies. The reasons put forward by these authors are that poor households consume more instead of investing in their future; their companies fail to produce enough profits to pay high interest rates; their longer-term investments are not sufficient to yield a fairly high return.

However, for Duflo and Parienté (2009), these controversies about the effects of microcredit on poverty are partly explained by certain methods used that omit selection bias. Taking a sample of 445 households from 14 villages in Thailand, Kyereboah-Coleman (2007) explains that this selection bias is due to the fact that the richest people have a higher probability of participating in a microfinance program. Similarly, the results of Hulme and Mosley (1996) and Khandker (2005) were respectively challenged for methodological and data quality reasons by Morduch (1999) and Roodman and Morduch (2009).

In view of the controversy surrounding the impact of microcredit on the poorest households and the methodological limitations often mentioned in the scientific literature, this article proposes to evaluate the impact of access to microfinance, which is the microcredit on the reduction of the level of poverty in Ghana. The choice of Ghana is justified by the fact that, despite the reduction in the poverty rate, there remains a chronic disparity in the poverty rate in different settings - the incidence of poverty in rural areas is 43.7% compared to 12.4%

in urban areas in 2005-2006 (service, 2014). Subsequently, various microcredit programs were implemented throughout Ghana.

Two major innovations are made by this paper compared to previous studies. First, it uses a national database and thus assesses the impact of microcredit in general and not in a particular way. This can guide public decision makers choices and better target those households which truly benefit from microcredit. Second, the results contribute to the controversial debate about the impact of microfinance on the poorest segments of the population. Indeed, through the quantile regression method, it is possible to know whether microfinance benefits more the poor or the rich.

The remainder of the paper is structured as follows: The second section discusses the methods used to assess the impact of microcredit on poverty, namely the *Propensity Score Matching* and *quantile regression*. The third section discusses the survey data used. The fourth section describes the analysis and interpretation of the results. Finally the fifth section concludes.

2 Methods

In this study, the main hypothesis tested is that access to microcredit reduces poverty. If the credit was randomly distributed to households (randomization), its impact would be measured by simply comparing the average of the poverty rate of beneficiaries with that of non-beneficiaries. However, since the decision whether or not to benefit from microcredit rests with households and microfinance institutions, a mere comparison of averages will result in erroneous results due to selection bias.

In the literature, two methods are used to solve this problem. The first is the method of matching the propensity score (PSM) in cases where the probability that an individual is treated depends on its observable characteristics, and the second, the method of the instrumental variables or model of Heckman in the case where this probability is related to unobservable characteristics (Becker et al., 2002). Imai et al. (2010) suggest that it is very difficult to find a valid instrument for the relative poverty index because it is an indicator that incorporates all aspects of household welfare. Therefore, we opt for the PSM method proposed by Rosenbaum and Rubin (1983).

2.1 The Propensity Score Matching (PSM)

The basic principle of this method is to compare individuals with the same observable characteristics in order to be able to identify the effect of a treatment. In view of the multidimensionality of the individual characteristics, it is recommended to calculate a propensity score which represents the probability that an individual will be treated given his / her characteristics. Estimating a probit or logit model provides these scores with variable $T = \{0, 1\}$ as the dependent variable. Precisely, this equation is estimated:

$$P(X) = Prob(T = 1|X) = E(T|X) \tag{1}$$

where the propensity score is the predicted probability of receiving treatment given the vector of characteristics X.

PSM assumptions

The PSM is based on two fundamental assumptions:

Existence of a comparison group:
$0 < Prob(T = 1X) < 1$
implying that each individual in the sample had a non-zero probability of being treated.

The Conditional Independence Assumptions (CIA) which states that given the characteristics of individuals, the probability of being treated is independent from the outcome (the selection effect is based only on observables)
$Y_0 \perp T|X E(Y_0|T = 1, X) = E(Y_0|T = 0, X)$

The choice of covariates

The choice of the variables that can explain the probability of being treated must follow a certain number of principles. Aichele and Felbermayr (2011) suggest that these variables explain both the probability of being treated and the outcome of treatment. On the other hand, for authors, there is no standard test for choosing these variables. For this study, these variables are selected on the basis of the literature and the conditions for granting microcredit in developing countries. Thus, socio-demographic variables such as age, sex, marital status, the dependency ratio, household size and literacy level that are likely to influence both access to microcredit and the level of poverty are included in the model. Moreover, the granting of microcredit is often conditioned by the possession of a guarantee which can be materialized by the possession of land or a remunerated work. The following probit model is estimated

$$T = X\beta + \epsilon_i \tag{2}$$

with T taking the value 1 if the individual has access to the microcredit and 0 otherwise. X is the vector of the covariates.

Estimating the treatment effect

The scores obtained although they make it possible to overcome the problem of multi-dimensionality, do not completely solve the problem of matching. Becker et al. (2002) show that the probability of observing two individuals with exactly the same score is virtually zero. Thus, they propose methods of pairing to estimate the average effect of a treatment on the treated individuals (ATT). This is the *Nearest-Neighbor matching, Statification matching, Kernel matching, Radius matching*. The first three approaches are used in this study. A complete description of these approaches can be found in Becker et al. (2002). These authors state that none of these methods is superior to the other. We then use these three estimation methods for robustness test purpose as recommended by the authors.

Once the matching problem is resolved, two types of effects can be estimated: The Average Treatment Effect (ATE) and The Average Treatment Effect on the Treated (ATT) which are given by the following equations:

$$ATE = \frac{1}{N_T}\sum_{i=1}^{N_T}(\hat{Y}_{i1} - \hat{Y}_{i0}) \tag{3}$$

$$ATT = \frac{1}{N_T}\sum_{i=1}^{N_T}(Y_{i1} - \hat{Y}_{i0}) \tag{4}$$

In addition to these three methods, that of quantile regression is also used to perform deeper analysis of the impact of microcredit on poverty reduction.

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2.2 Quantile regression

One of the goals of microcredit is to provide financial means to the poorest groups excluded from the traditional financial system. If this goal is indeed achieved, microcredit should have a much greater impact on the poorest people. The quantile regression can verify this assertion. The impact of microcredit is then estimated at different quantiles of the poverty index distribution.

Two main approaches can be used for this purpose: Abadie et al. (2002) and Firpo (2007). In this study, the Firpo (2007) approach is used insofar as the LPN assumes an endogenous treatment linked to unobservables and thus requires the use of instrumental variables. The assumption of non-nullity of the probability of being treated and that of conditional independence are also necessary for the application of this approach.

The objective is to estimate the treatment effect on the distribution of the outcome, the treatment effect on the ρ^{th} quantile is given by (Dhaultfœuille and Givord, 2014):

$$QTE = Q_{Y_1}(\rho) - Q_{Y_0}(\rho) \tag{5}$$

$Q_{y_1}(\rho)$ and $Q_{Y_0}(\rho)$ represent the values of ρth quantile if the group is treated or not. It is obvious that these two values cannot be observed simultaneously. On the other hand, the treatment effect on the quantiles of the treated group can be estimated. It is a question of seeking the difference of poverty distribution between the treated and the untreated groups. This difference is the Quantile Treatment Effect on the Trated (QTET) and is given (for the ρth quantile) by:

$$QTET = Q_{Y_1}(\rho|T=1) - Q_{Y_0}(\rho|T=1) \tag{6}$$

Firpo (2007) shows that these conditional quantiles $Q_{Y_1}(\rho|T=1)$ and $Q_{Y_0}(\rho|T=1)$ can be identified from the variables X, T and Y such that:

$$\rho = E[\frac{T1(Y \leq Q_{Y_1}(\rho))}{P(X)}] \tag{7}$$

$$\rho = E[\frac{(P(X)}{1-P(X)}\frac{(1-T)1(Y \leq Q_{Y_0}(\rho))}{P}] \tag{8}$$

X, Y and T respectively represent the observable characteristics of the individuals, the outcome and the treatment variable The importance of this result is that the only function to be estimated is $P(X)$ which is the propensity score. Formally, the method consists of two steps:

a first step where the propensity scores are estimated as in the PSM method. In the second step, we estimate $Q_{Y_1}(\rho)$ and $Q_{Y_0}(\rho)$ as follows:

$$\hat{Q}_{Y_t}(\rho) = argMin \sum_{i=1}^{i=n} \omega_{t,i} \tau_\rho (Y_t - b) \tag{9}$$

with $\omega_{1,i} = \frac{T_i}{p(X_i)}$ and $\omega_{0,i} = \frac{1-T_i}{1-p(X_i)}$

This is similar to regress the variable Y_t on a constant b by taking care to weight each observation by the inverse of the probability of being treated and that not to be treated, respectively for the treated and the untreated groups.

The impact of the treatment on the ρ^{th} quantile of the treated group is given by:

$$\hat{Q}TET = Q_{Y_1}(\rho) - \hat{Q}_{Y_0}(\rho) \tag{10}$$

3 Data

3.1 Data source and variable measurements

The initial database originates from a survey commissioned by the World Bank and the International Fund for Agricultural Development (IFAD) from February to June 2004. On the basis of these data, Imai et al. (2010) calculated a number of indicators of household living conditions, including the relative poverty index, which is our measure of household poverty.

Poverty in living conditions is reflected in a lack of housing, health, food and education (Koloma et al., 2007). The relative poverty index is one measure of this poverty situation. This is a composite index that has been determined to differentiate between the *poorest* group and the *less poor* households in the sample (Imai et al., 2010). The approach used to measure this index is the Microfinance Poverty Assessment Tool (MPAT), which uses consumption data to construct a multidimensional index (Henry et al., 2003). This approach is based on the Principal Component Analysis (PCA) and assumes that the degree of relative poverty of a respondent relative to other participants can be assessed from well-being variables such as housing conditions, food security and vulnerability, livestock and consumer assets (Imai et al., 2010). The composite index is therefore calculated at the household level. The treatment variable (access to microcredit) and the covariates are described in Table 1

Table 1: Variable description

Variables	Descriptions
Poverty index	value from -3 to 3
Access to microcredit	1 if the household is a client of a microfinance institution and has received a loan and 0 otherwise
Area	1 if household lives in urban areas and 0 if living in rural areas
Sex	1 if the head of household is a woman and 0 if he is a male
Age	Age of household head
Employment	1 if the head of household has a job and 0 otherwise
Land	1 if household own land and 0 otherwise
Literate	1 if the head of household knows how to read and write and 0 otherwise
Marital status	1 if the head of household is a couple and 0 otherwise
Household Size	Number of People Living in Household
Dependency ratio	Ratio between the number of people who do not work and the number of those who work

3.2 Descriptive statistics

Table 2 presents the descriptive statistics of some variables in the model. These statistics show differences in access to microcredit and poverty index according to household characteristics. The analysis shows that more than half of respondents received credit during the reference period. Indeed, 56.42% state that they have received a microcredit. Further analysis suggests that the proportion of urban residents with microcredit (62.05%) is higher than that in rural areas (51.27%). More specifically, for loan recipients, an analysis by area of residence indicates that men residing in rural areas receive more credit compared to women. Thus, microcredit seems more intended for men in these rural areas.

An analysis of poverty index statistics among both loan recipients and non-recipients shows that the poorest households live in rural areas. Indeed, among the beneficiaries, there is a significant gap in the average poverty indices, which in rural and urban areas are respectively -0.41 and 0.83. Among non-beneficiaries, the urban poverty index of 0.78 is relatively higher than that of rural residents (-0.48).

The overall gender analysis does not point to any significant differences in access to micro-credit between men and women. The poverty index shows that women are relatively less poor than men in either the beneficiary or the non-beneficiary group in that their poverty index is twice that of men. This situation also prevails in rural areas. On the other hand, in urban areas, the average poverty index of men (0.86) is higher than that of women (0.59). In rural as well as in urban areas, the majority of heads of households receiving microcredit are employed. However, this rate is higher among urban residents. In addition, less than half of the non-microcredit recipients have jobs regardless of their place of residence. Thus, employment appears to be an important criterion to access to microcredit in the same way as land possession. Indeed, the proportion of credit recipients owning land is higher than that of those who do not. The most important finding is the very large difference in the average poverty index between the beneficiary and the non-beneficiary groups. This positive difference leaves a potential impact of microcredit on the poverty index.

Table 2: Descriptive statistics

Variables	Access to microcredit		No access to microcredit		All	
	%(number)	Poverty index	%(number)	Poverty index	%(number)	Poverty index
Women	**54.78 (361)**	**0.31**	**45.22 (298)**	**0.11**	**100 (659)**	**0.22**
Rural	45.07 (128)	-0.28	54.93 (156)	-0.31	100 (284)	-0.30
Urban	62.13 (233)	0.64	37.87 (142)	0.59	100 (375)	0.62
Men	**56.95 (1 172)**	**0.16**	**43.11 (886)**	**0.05**	**100 (2 058)**	**0.11**
Rural	52.82 (599)	-0.56	47.18 (535)	-0.49	100 (1 134)	-0.52
Urban	62.01 (573)	0.91	37.99 (351)	0.86	100 (924)	0.89
Employment	**58.10 (1 452)**	**0.11**	**41.90 (1 047)**	**0.02**	**100 (2 499)**	**0.11**
Rural	52.65 (705)	-0.52	47.35 (634)	-0.48	100 (1 339)	-0.50
Urban	64.40 (747)	0.84	35.60 (413)	0.79	100 (1 160)	0.82
No Employment	**37.16 (81)**	**0.50**	**62.84 (137)**	**0.42**	**100 (218)**	**0.45**
Rural	27.85 (22)	-0.17	72.15 (57)	-0.03	100 (79)	-0.07
Urban	42.45 (59)	0.74	57.55 (80)	0.74	100 (139)	0.74
Possess a land	**60.55 (910)**	**-0.02**	**39.45 (593)**	**-0.26**	**100 (1 503)**	**-0.11**
Rural	56.11 (542)	-0.65	43.89 (424)	-0.64	100 (966)	-0.64
Urban	65.53 (368)	0.91	31.47 (169)	0.69	100 (537)	0.84
Don't Possess a land	**51.32 (623)**	**0.52**	**48.68 (591)**	**0.39**	**100 (1 214)**	**0.46**
Rural	40.93 (185)	-0.09	59.07 (267)	-0.14	100 (452)	-0.12
Urban	57.48 (438)	0.77	42.52 (324)	0.83	100 (762)	0.80
Total	**56.42 (1 533)**	**0.20**	**43.58 (1 184)**	**0.07**	**100 (2 717)**	**0.14**
Rural	51.27 (727)	-0.51	48.73 (691)	-0.45	100 (1 418)	-0.48
Urban	62.05 (806)	0.83	37.95 (493)	0.78	100 (1 299)	0.81

4 Results and Discussions

4.1 Propensity scores

Table 3 illustrates the estimation results of the determinants of access to microcredit in rural, urban and national areas. The value of the likelihood ratio for each of the three estimates is high, indicating that the models are globally significant. It appears from the estimation that age, household size, ownership of land and employment of household head and being a couple increase the probability to access to microcredit irrespective of the place of residence. In addition, microcredit programs appear to be more female-oriented, but only in urban areas. Indeed, women are 7.4% more likely to benefit from microcredit than men in urban areas. These results are consistent with those of Imai et al. (2010).

In addition, the guarantee is an important factor explaining the access to microcredit as, on a national level, ownership of land and employment increase the probability of receiving microcredit by 8.8% and 14.8%, respectively. This result highlights the paradox surrounding the microfinance system in developing countries. Indeed, microfinance is meant to be targeted to the poor who have no guarantee and are excluded from the traditional financial system. However, access to its most important product, microcredit, is often subject to warranty conditions.

The majority of the variables selected have a significant influence on the probability of benefiting from microcredit, thus indicating relevance in the choice of characteristics. The calculated scores can thus be used in the second part of estimation. The imposed common supports for total and areas of residence are large enough to provide a relatively high sample to be included in this second stage.

Table 3: Probit model

Varibales	Total			Rural			Urbain		
	Coef	Z	dF/dx	Coef	Z	dF/dx	Coef	Z	dF/dx
Gender	0,252***	3.22	0,098	0,183	1.51	0, 073	0,198*	1.86	0,074
Age	0,067***	5.72	0,026	0,102***	6.12	0, 041	0,032*	1.89	0,012
Age^2	-0,001***	-5.91	-0,002	-0,001***	-6.13	-0, 001	-0,001**	-2.11	-0,001
HH Size	0,001	0.02	0,001	-0,002	-0.15	0,001	0,006	0.35	0,002
Literate	0,042	0.79	0,016	-0,067	-0.92	-0,027	-0,122	-1.28	-0,046
Land	0,223***	4.27	0,088	0,337***	4.39	0,134	0,230***	3.87	0,111
Employment	0,372***	3.83	0,148	0,395***	2.35	0,155	0,461***	3.68	0,180
Marital status	0,375***	4.62	0,148	0,469***	3.78	0,184	0,312***	2.83	0,121
Dependency	-0,052	-0.43	-0,021	-0,142	-0.81	-0,057	0,150	0.84	0,057
Constant	-2.199***	-7.58	-	-3,348	-7.6	-	-1,162	-2.85	-
Observations	2 717			1 418			1 299		
LR	chi2(9)=130.11			chi2(9)=112.46			chi2(9)=62.23		
Pseudo R^2	0.035			0.057			0.036		
Common Support	[0,10 ; 0,77]			[0,13 ; 0,75]			[0,20 ; 0,82]		

****=significant at 1% ; **=significant at 5% ; *=significant at 10%; dF/dx=Marginal effects

4.2 The impact of microcredit on household poverty index

The impact of the microcredit presented in Table 4 was estimated with the propensity scores obtained in the first part by imposing the common support. Three methods of matching were used for this estimation, including the Nearest-Neighbor Matching method, the Stratification Matching method, and the Kernel Matching method. In order to obtain robust coefficients, the bootstrap procedure was used with 100 replications.

For the sample as a whole, the results indicate that access to microcredit reduces relative poverty, regardless of the matching method used. These results corroborate those of Imai et al. (2010), Imai et al. (2012) and Bangoura and Hounwanou (2015). A detailed analysis reveals that this impact is more pronounced for Nearest-Neighbor Matching (0.184) and Stratification Matching (0.183) than for Kernel Matching (0.167). In view of the shortcomings of the Nearest-Neighbor Matching method compared to the other methods, the results obtained by these methods will be analyzed [1] Analysis by place of residence suggests that access to microcredit has no significant impact on rural poverty. On the other hand, in urban areas, the impact of microcredit on household relative poverty index is estimated at 0.069, reflecting an improvement in their living conditions. Moreover, this effect is less than that found at the national level. Since poverty is predominantly rural in most developing countries, the results suggest that microcredit benefits the richest. This conclusion differs from that of Imai et al. (2010) and corroborates the schism hypothesis of microfinance denounced by Servet (2009), Morduch (2000) and Woller et al. (1999). It also raises the question of the success of the activities for which the microcredit has been granted. Indeed, income-generating activities, which are the main vocation of microcredit, are more likely to succeed in urban than in rural areas because of the enabling environment for business.

It is important to note that the interpretation of the results must be done with caution insofar as the poverty indicator used does not discriminate between poor and non-poor households. Thus the impact obtained does not make it possible to say whether access to microcredit has enabled some households to emerge from poverty. This caution should not, however, obscure the fact that the estimated impact reflects an improvement in the living conditions of the beneficiary households. Indeed, it is fair to say that access to microcredit has improved the situation of beneficiary households compared to non beneficiary households

[1] For Becker et al. (2002), the nearest neighbor method presents the risk of matching of individuals with very different characteristics, leading to a possible overestimation (underestimation) of the effects of the program.

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Table 4: Impact of microcredit on household poverty index

Methods	Treatment Group	Control Group	Coefficients	Z
Nearest-Neighbor Matching (attnd)				
Total	1 533	734	0.184***	3.47
Rural	727	373	0.157**	2.41
Urban	806	344	0.106**	2.53
Stratification Matching (atts)				
Total	1 533	1 178	0.183***	4.18
Rural	727	667	0.026	0.44
Urban	806	491	0.075**	2.30
Kernel Matching (attk)				
Total	1 533	1 178	0.167***	4.42
Rural	727	667	0.022	0.41
Urban	806	491	0.069*	1.95

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

4.3 The impact of microcredit through quantile regression

Table 5 presents the results of the quantile regression microcredit impact on the relative poverty index. This impact was estimated on the quartiles in order to have a sufficiently high sample in each group. First, the optimal values of the bandwidth and the λ parameter used for the smoothing of the continuous variables and the dummy variables respectively were estimated using the method proposed by Frölich and Melly (2010). These values were subsequently included in the quantile regression. As stated by Firpo (2007), the coefficients obtained cannot be interpreted as effects on the individuals of the quantile in question unless we assume that the hypothesis of rank invariance is satisfied. For this article, this would mean assuming that the ranking of individuals according to the relative poverty index has not changed following treatment. Dhaultfœuille and Givord (2014) consider that this hypothesis is very restrictive in most cases of impact assessment. In this case, precisely where the index of poverty is relative the same ranking on the basis of this index cannot prevail after treatment. Considering the entire sample, the results indicate that microcredit has an effect on the distribution of the relative poverty index. Indeed, access to microcredit increases the median and the last quartile of the relative poverty index by 0.23 and 0.17 respectively. In other words, the maximum relative poverty indices in the group of individuals in the second and last quartiles have been increased. On the other hand, microcredit has no impact on the first quartile. This result reflects an increase in inequalities in the treatment group. Iinequalities are of two kinds. First, the results highlight an increase in intra-quartile inequalities for individuals in the second quartile so that the poverty index of the poorest individual has not changed while that of the less poor has increased. Second, cross-quartile inequality has grown among the beneficiaries of microcredit. Indeed, the distribution of the relative poverty index between the richest individuals (last quartile) has become less inegalitarian than that of the poorest individuals (first quartile) because of access to microcredit. An estimate by place of residence indicates that access to microcredit has no impact on the distribution of the relative poverty index in rural areas. In urban areas, although the first two quartiles are not influenced by microcredit, the last quartile is positively impacted by microcredit, reflecting an improvement in the living conditions of the richest individuals and a reduction in inequalities in this category of households. The results obtained by the quantile regression confirm those of the PSM insofar as the distribution of the poverty index is in no way influenced in rural areas whereas it is in urban areas. Moreover, the results raise one of the controversies in the literature that microfinance benefits the rich rather than the poor (Hulme and Mosley, 1996). The empirical evidence observed in Table 5 confirms this point of view. Indeed, the invariability of the first quartiles and the rise of the last quartiles reflect the fact that the 25% of the richest households have their situation improve due to access to microcredit when it is not necessarily the case for the poorest 25%. This could be explained in the present case by the amount of the loan obtained. Indeed, the data do indicate that the average loan size of the richest 25% is eight times higher than that of the poorest 25%.

Table 5: Impact of microcredit on the relative poverty index distribution

Quantiles	Total		Rural		Urban	
	Coefficient	Z	Coefficient	Z	Coefficient	Z
1^{st} quartile	0.09	0.79	0.02	0.17	0.08	1.06
2^{nd} quartile	0.23***	3.46	-0.06	-0.51	0.07	1.54
3^{rd} quartile	0.17***	3.91	0.11	1.41	0.12***	3.18
Observations	2 716		1 417		1 299	
Bandwidth	2		1		1	
Lambda(λ)	2		1		1	

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

5 Conclusion

In this paper, we examined the impact of micro-credit access on household poverty based on survey data. The tested hypothesis is that microfinance has no impact on the level of poverty. An index reflecting the multidimensional aspects of poverty was used as an indicator of poverty. To account for the selection bias due to the non-randomness of access to micro-credit, the propensity score is used to assess the effect of access to microcredit on poverty. In addition, quantile regression has been used to verify one of the objectives of microcredit, namely to provide financial means to the poorest groups excluded from the traditional financial system.

The results of the Probit regression indicate that age, marital status, having a job, land ownership and being a woman increase the likelihood of accessing microcredit in Ghana. The dependency ratio negatively influences the probability of obtaining a microcredit.

As far as impact is concerned, the results show that access to microcredit plays an important role in reducing poverty, thus reversing our hypothesis and corroborating the results of Imai et al. (2010), Imai et al. (2012) and Bangoura and Hounwanou (2015). A disaggregation of the impact of the microcredit program in rural and urban areas shows that it is more important for households in urban areas and nil in rural areas. This suggests that microcredit benefits the richest while poverty is predominantly rural. The same result is confirmed with quantile regression, thus corroborating the controversy of mission drift of microfinance in the literature. The quantile regression concludes that the 25% of the richest households in the sample see their situation improving with microcredit, whereas in the poorest 25%, microcredit access has no impact on poverty index. Given that the average amount of credit received by households in the last quartile is eight times that received by the first quartile, one of the prospects for further study would be to examine the impact of microcredit on poverty through the *dose response* method.

The results obtained are relatively robust in terms of the impact of microcredit on the population as a whole. Despite this, it remains a limit in this study. Indeed, the probability of benefiting from microcredit could be related to the unobservable characteristics of households. Therefore so the Heckman instrumental variables method could have been used.

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