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Is the Microfinance Effective for Everyone?

소액금융은 모두에게 효과적인가?

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Graduate School of Social Sciences
Seoul National University
Economics Major

MinKyung Kim

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MinKyung Kim[1*]

[1]Department of Economics, Seoul National University
1 Gwanak-ro Gwanak-gu, Seoul

[*]E-mail: kmk7699@snu.ac.kr

Abstract

This paper measures treatment effects of microfinance programs on poverty using panel data of Bangladesh. In most previous studies, microfinance programs were evaluated based on mean-analysis, using only the traditional poverty indices such as headcount measure. However, measuring the impact of microfinance over the whole population would give us more information on how people from different socioeconomic status are affected. Therefore, after applying the fixed-effects model which measures for the mean effects, I use the stochatic dominance approach to measure the effect of microfinance programs all over the distrubution by generating counterfactual consumption distributions. I could not find evidence that microfinance alleviates poverty in all consumption levels after controlling for the self-selection bias. Improvements in consumption poverty in terms of traditional poverty indices also disappears after the control.

Keywords: Microfinance, Poverty, Poverty Indices, Fixed-effects method, Stochastic dominance, Distributional treatment effect, Counterfactual distributions

Contents

1 Introduction

This paper explores the widely studied yet baffling facet of anti-poverty policies: microfinance. It is the single most influential anti-poverty program throughout the world, but its treatment effects still remain controversial. Microfinance has been the most extensive anti-poverty program supported by lots of governments and NGOs since the 1970s. It allows the poor to get access to credit at reasonable interest rates. It is intended to support small-scale businesses, and allows for consumption smoothing and risk managements. However, the effect of microfinance is known relatively little compared to its widespread use. This paper tries to estimate the impact of microfinance on consumption poverty. The datasets are from Bangladesh household surveys in 1992 and 1999.

Bangladesh has a number of microfinance organizations, including the Grameen bank of Muhammand Yunus, the world's most famous microfinance organization. Bangladesh has more than 500 microfinance provides and surveys indicate that more than one third of Bangladesh rural households participate in at least one of the programs. However, the operation costs are so high that it is hard for microfinance lenders to sustain their program without relying on donors. In Bangladesh, governments and donors willingly provide support for microfinance with the belief that it helps the poor.

However, after the attention towards microfinance rose due to Muhammad Yunus's winning of the Nobel prize, there have been concerns that microfinance programs have limited or no effect in improving lives of the poor. It

is important to figure out the impact of microfinance since the government's and donors' supports could be used for other anti-poverty programs, if microfinance is found not to be effective.

The effect of microfinance on consumption poverty has not reached an accordance. Khandker (2005) presents evidence that microfinance contributes to poverty reduction, and women's participation is especially important for consumption increase. He used the headcount ratio in measuring the effect of microfinance in poverty. As we will see below, headcount ratio omits information on how severe the poverty is since it only counts the number of people under the poverty line. Furthermore, his analysis based on a regression method draws out the results on only the mean level, so we cannot guarantee that the effects of microfinance exists all over the consumption distribution. Angelucci et al (2013) also propose that microfinance provides better liquidity and risk managing for participants. However, they find little evidence of income or consumption improvement on average. sEven the small, insignificant increase disappeared after 2 years. Hulme and Mosley (1996) suggest that households with initial income above the poverty line benefited from microfinance while poorer houses did not. They showed different treatment effects across different groups.

My research concerns the distributional effect of microfinance, as poverty cannot be fully captured with finite moments such as mean or variance. Stochastic dominance tests are useful in comparing distributions since they provide uniform ordering of prospects under weak utility assumptions. I measure

treatment effects of microfinance programs in poverty in terms of consumption, conducting both the fixed-effects regression and stochastic dominance tests. Stochastic dominance test is especially appropriate for measuring poverty issues, since it provides evidence of consistent treatment effects across different groups. Also, stochastic dominance test directly links to Foster-Greer-Thorbecke poverty indices which gives weight on income gaps, satisfying basic axioms that poverty indices should meet. Traditional poverty measures like headcount ratio and normalized poverty deficit do not meet all of these axioms.

This paper uses the same household panel data in Khandker and Pitt (2003) and Khandker (2005). First, it examines whether microfinance has a positive effect on consumption using the fixed effects regression. Then, I show the distributional effects of microfinance on poverty using stochastic dominance approach. Finally, I show the aggregate poverty effect of microfinance using various poverty indices including headcount ratio, normalized poverty deficit, and Foster-Greer-Thorbecke poverty indices.

2 The Data and Characteristics

It is difficult to measure the effect of microfinance, since there could be endogeneity in selection of program groups and participation within the groups. Usually, program areas are chosen so that the expected benefit of microfinance

is high - where poverty is prevalent and people have difficulty getting access to credits. Also, people who participate in microfinance may have higher entrepreneurial abilities than those who don't. Therefore, it is important to get rid of these endogeneities.

In this paper, I try to take these endogeneities into consideration by using a carefully designed panel survey from the BIDS-World Bank. The data set is available online at :
http://microdata.worldbank.org/index.php/catalog/1317/download/24078. The survey covered project areas of BRAC, Grameen Bank, and Bangladesh Rural Development Board's Rural Development 12 program (RD-12). In this survey, both program villages and non-program villages are drawn randomly, and households were sampled from both program and non-program villages. Households who had more than half an acre of land, thus not eligible for the microfinance in Bangladesh were also included. Therefore, I can identify the effect of microfinance by comparing participants and nonparticipants among who are eligible for the program.

The survey took place for 3 times in 1991/1992, covering 1,789 households, 87 villages, and 29 thanas. Since there are attritions as the survey went on, the last round data only include 1,769 households. The survey was conducted again in 1998/99, which includes the households who participated in the 1991/92 surveys, new households from original villages, and households from new villages. The total number of households is 2,626, but there are households separated from the 1991/92 households. These households are

merged in analyses because one-to-one correspondence between households was needed.

Table 1: Program eligibility rate and participation rates, 1992/1999 (%)

	1992	**1999**
Non eligible households	259(14.6%)	371(14.1%)
Eligible households	1,510(85.4%)	2,255(85.8%)
Participants	622(35.2%)	1,655(63.0%)
Non-participants	888(50.2%)	600(22.8%)
Total households	1,769	2,626

In 1992, 1,510 households among 1,769 households were eligible to participate in the microfinance program of BRAC, Grameen Bank, or BRBD. 622 households participated in one of those programs. In 1999, the eligibility rate stayed almost the same, between 85 and 86%, but the participation rate went up from 35.5% to 63.0%, almost 30% of households joining the microfinance programs.

Total household consumption is measured as the sum of expenditures on food and non-food items, excluding expenditures on business since business investments do not directly improve the quality of living in the short run. Household daily per capita consumption grew 70.8% over the seven years. Estimating consumption effects captures the main objective of microfinance programs. Although microfinance may not be useful in increasing business investments or business incomes, it still serves its purpose if it helps the poor

to manage their cash flow so they can maintain constant consumption level over time, and even increase consumption level ultimately.

3 Effects of microfinance loan on consumption: Fixed effects method

In assessing the impacts of microfinance on consumption, the key problem is the endogeneity rising from voluntary parcitipation in the programs. To solve for the problem of non-random participation of households, we can apply the fixed effects methods. Fixed effects method rules out the self selection effect since it fixes for unobserved household characteristics that might lead to participation such as entrepreneurial ability and the poverty incidence in villages. Therefore, I consider household-level fixed effects and village-level fixed effects in order to get rid of those effects.

Consider the following model of per capita consumption by the household i, living in village j, in time period t.

$$C_{ijt} = X_{ijt}\lambda + S_{ijt}\delta_1 + S_{ij(t-1)}\delta_2 + \mu_{ij} + \eta_j + \epsilon_{ijt}$$

where C is per capita household consumption, X is a set of household characteristics such as the age of the head, sex of the borrower, marital status of household head, and so on. S is the amount of borrowing from microfinance institutions, μ is the household-level fixed effect, and η stands for the

village-level fixed effect. Borrowing from the previous period is also included in the regression. Borrowing from the past influences the amount of spending today since people might not use up all their borrowing instantaneously, or they might have to pay back their loans from the past.

Table 2: Fixed-effects results of the impact of microfinance on household consumptions

Independent variables	**Log of per capita consumptions**
Log of household borrowing	0.0157^{**}
Log of past household borrowing	-0.0167^{*}
Female borrower	0.2134^{**}
Age of household head	0.0089^{**}
Years of formal education (head)	0.0133^{*}
Years of formal education (father)	-0.0005
Years of formal education (mother)	-0.0024
Household head is married	-0.2409^{**}
Number of household members	0.0836^{**}
Amount of land (Decimals)	0.0000

**T-statistic is significant at the 1% level or lower.
*T-statistic is significant at the 5% level or lower.

The fixed-effects model above provides little evidence that the household borrowing from microfinance institutions increases the per capita household consumptions. Although 1% increase in the current household borrowing increases the per capita household consumptions by 1.57%, the household

borrowing from the last period decreases the per capita household consumptions by 1.67%. This result indicates that only the current borrowing has positive impacts on consumption. The negative coefficient of past household borrowing can be interpreted as a kind of mental accounting. People tend to separate their money into different accounts in their minds, so that they treat each account differently. Since their past borrowing and current borrowing are put into separate mental accounts, people reduce their current consumption if they have borrowed more in the past. When the borrower of the microfinance loan is female, per capita household consumption increases by 21.34%, which supports the claim that female borrowers are better targets for microfinance programs. Age of household head and years of education also have positive impacts on household consumptions, but the effect of education wanes as it goes up to the former generation. The coefficients of parents' formal education is slightly negative, but they are statistically insignificant. Households with married household head appears to have significantly lower consumptions and households with more members consume more. Finally, amount of land has no effect on household consumptions.

4 Distributional effect of microfinance: Stochastic Dominance Approach

Although the fixed-effects method reveals some positive effect of microfinance loans on consumptions, we cannot get the overall picture of how the microfinance effects people with different levels of consumptions. In this section, I will analyse the distributional effect of microfinance using the stochastic dominance approach. Stochastic dominance is a useful way to compare different distributions because it determines the rankings of distributions under moderate assumptions such as increasing and concave utility functions. It does not impose any restrictions about the parametric model that distributions should follow, so stochastic dominance can be used for comparing a wide variety of distributions.

4.1 Testing for stochastic dominance of consumptions between participants and non-participants

Separating the effects of microfinance can be partly done by comparing participants and non-participants, both who were eligible to participate in the program. Program eligibility is decided by the amount of land households own. Being eligible to participate in microfinance programs indicates that both groups are poor enough to get access to microfinance programs. Since the selection of households and villages was not random, systematic bias is expected for these two groups including the self-selection bias which arises when deciding to participate in the program or not, and the characteristics of

the villages themselves. These biases will be corrected in the next section, using a different approach.

To test whether there exists stochastic dominance relationship between consumptions of participants and non-participants, I use Barett and Donald's Kolmogorov-Smirnov type test. Let $F_1^{(1)}(x) = \int_0^x f_1(t)dt$ where $f_1(x)$ is the distribution function of consumptions of non-participants, and $F_2^{(1)}(x) = \int_0^x f_2(t)dt$ where $f_2(x)$ is the distribution function of consumptions of participants. Define $F_k^{(s)}(x) = \int_0^x F_k^{(s-1)}(t)dt = \frac{1}{(s-1)!}\int_0^x (x-t)^{s-1} f_k(t)dt$. Then, the hypothesis of interest are

$$H_0 : F_1^{(s)}(x) \leq F_2^{(s)}(x), \forall x \in X$$

$$H_1 : F_1^{(s)}(x) > F_2^{(s)}(x) \; for \; some \; x \in X.$$

Here, I consider the null of dominance against non-dominance, which is used by most of the stochastic dominance literature. When the null hypothesis is rejected, there exist statistical evidence that indicates the consumptions of microfinance program participants are not stochastically dominated by that of non-participants. Otherwise, if the null hypothesis cannot be rejected, it might indicate that the consumptions of non-participants stochastically dominates the consumptions of participants unless the result is due to a lack of power.

The test statistic is $BD_1 = \sqrt{\frac{n_1 n_2}{n_1+n_2}} \sup_{x \in X}(\bar{F}_1^{(s)}(x) - \bar{F}_2^{(s)}(x))$, where $\bar{F}_k^{(s)}(x) = \sqrt{\frac{n_1 n_2}{n_1+n_2}} \sum_{i=1}^{n_k} \frac{1}{(s-1)!}(x - X_{ki})^{s-1} \mathbb{1}[X_{ki} \leq x] \; for \; k = 1, 2.$

Then, we can get p-values of the test by using bootstrap methods. In this paper, I used the pooled bootstrap which generates pooled sample of the two distributions and independently select two bootstrap samples from this pooled

sample. The empirical CDF of the bootstrap samples are used to compute the p-values of the test. The number of bootstrap simulations is 10,000. The reversed test is also conducted as well. The test results are as follows.

Table 3: Test of stochastic dominance on participants'/ non-participants' consumptions in years 1991/92

		P-value	
Years	**Null hypothesis**	**FOSD**	**SOSD**
1991/92	$F_1 \leq F_2$	0.864	0.754
	$F_2 \leq F_1$	0.000	0.000
1998/99	$F_1 \leq F_2$	0.000	0.000
	$F_2 \leq F_1$	0.999	0.875

The empirical CDFs show that the CDF of target non-participants' consumptions lies below the empirical CDF of target participants' consumptions in years 1991/92, but the relationship completely changes in years 1998/99. The stochastic dominance test results also gives the same results. We cannot reject the first order stochastic dominance and second order stochastic dominance of target non-participants' consumption over participants' consumption in years 1991/92 while we can reject the FOSD and SOSD of non-participants over participants at the significance level of 5%. On the reversed test, we can reject the stochastic dominance of participants' consumption over target non-participants' consumption in the first order and also in the second order in years 1991/92. However, we cannot reject the stochastic dominance of partic-

Figure 1: EDFs of target non-participants' and participants' consumption in years 1991/92

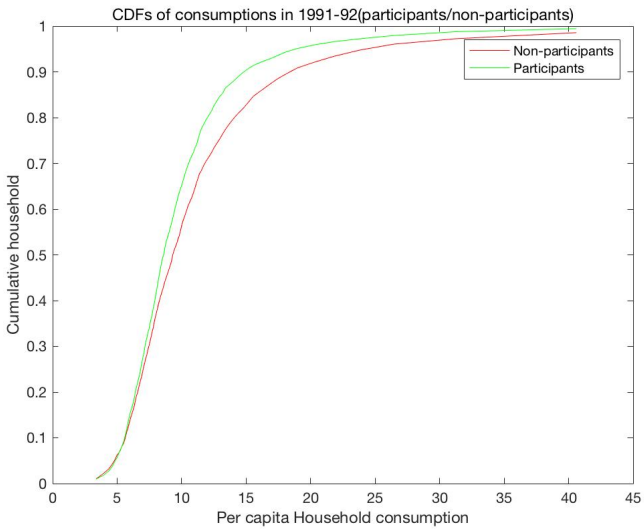
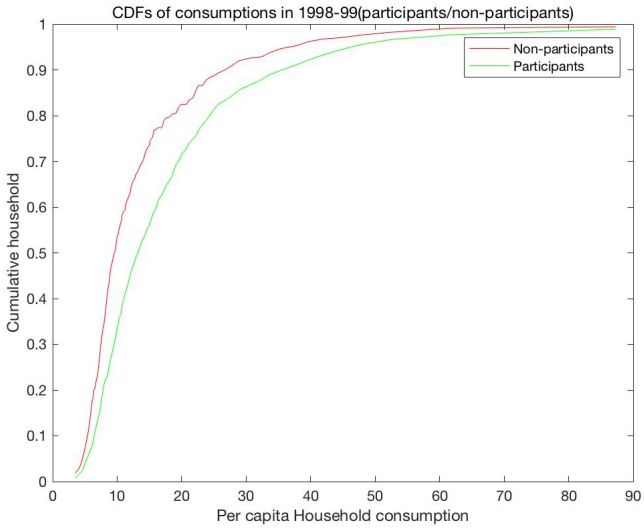


Figure 2: EDFs of target non-participants' and participants' consumption in years 1998/99



ipants' consumption over non-participants' consumption in years 1998/99.

This indicates that the effects of microfinance programs do not appear in the years 1991/92 but begin to emerge after some time has passed in 1998/99. Consumption of those who did not participate in the microfinance programs used to have lower consumption levels all over the distribution than those who did participate in the microfinance programs in 1991/92. This is thought to be caused by the self-selection bias. At the early stage of microfinance programs, those who are poorer than others may have been more likely to participate in the programs and get the loans. As the microfinance programs become widespread and settled down as a regular method of finance, its effects on consumption seems to rise.

However, since the self-selection bias and other potentially influencing variables such as the gender of participants is not considered, this result cannot be used for complete identification of the impact of microfinance programs on consumption and we need other approches that can take account of these problems.

4.2 Comparing counterfactual distributions with and without the treatment

As mentioned above, the standard stochastic dominance approach cannot get rid of the self-selection effect. Here, I resolve this problem by applying the method of Abadie (2002), which uses a binary instrument variable to generate

counterfactual distribution functions of outcome with and without the treatment. He proposes the method to generate counterfactual distributions which are identified by the compliers whose potential treatment status are affected by a binary instrument variable. To elaborate, his idea is to use the instrument variable Z that is independent of the outcome Y but is correlated with the treatment indicator D. Denote $Y(0)$ the potential outcome without treatment and $Y(1)$ be the potential outcome with treatment. $D(0)$ stands for the treatment status when $Z = 0$, and $D(1)$ is the value D would have taken when $Z = 1$. If we could generate the distribution of subpopulation who would participate in treatment if $Z = 1$ and do not participate if $Z = 0$ (we call them "compliers"), we can identify the causal effect of the treatment.

He verified that the difference between counterfactual distributions with and without treatment of these compliers is identical to the multiple of difference between distributions of outcome variables conditional to $Z = 1$ and $Z = 0$.

$$F^c_{(1)}(y) = E[\mathbb{1}\{Y_i \leq y\}D_i | D_i(1) = 1, D_i(0) = 0]$$

$$F^c_{(0)}(y) = E[\mathbb{1}\{Y_i \leq y\}(1 - D_i) | D_i(1) = 1, D_i(0) = 0]$$

$$F^c_{(1)}(y) - F^c_{(0)}(y) = \frac{E[\mathbb{1}\{Y_i \leq y\}|Z_i = 1] - E[\mathbb{1}\{Y_i \leq y\}|Z_i = 0]}{E[D_i|Z_i = 1] - E[D_i|Z_i = 0]}$$

Using the data of Bangladesh's microfinance programs, I used program eligibility as the binary instrument variable. Eligibility is closely related to the treatment, because only the eligible households were allowed to participate in microfinance programs. Eligibility of the program was decided by the amount

of land households own. Land is usually a highly illiquid asset, and there is no active land market in Bangladesh. In addition, looking back at the fixed effects method section, the regression result shows that the coefficient of land with respect to the consumption is insignificant and its coefficient is very close to zero. This can justify that eligibility, that is determined by amount of land, is independent to the outcome, which is consumption here.

I implemented the Kolmogorov-Smirnov type stochastic dominance test from section 4.(1) to counterfactual distributions, using the pooled bootstrap. $G_1^{(s)}(x)$ now becomes the counterfactual distribution of non-participants while $G_2^{(s)}(x)$ is the counterfactual distribution of participants. The number of bootstrap simulations is 10,000 and the reversed test is also conducted as well. So, applying for Abadie's method using program eligibility as an instrument variable, I get the following results.

Table 4: Test of stochastic dominance on counterfactual participants' and non-participants' consumptions

		Rejection probability	
Years	**Null hypothesis**	**FOSD**	**SOSD**
1991/92	$G_1 \leq G_2$	0.998	0.853
	$G_2 \leq G_1$	0.000	0.000
1998/99	$G_1 \leq G_2$	0.694	0.662
	$G_2 \leq G_1$	0.662	0.009

Figure 3: Counterfactual CDFs of consumption with and without microfinance in 1991/92

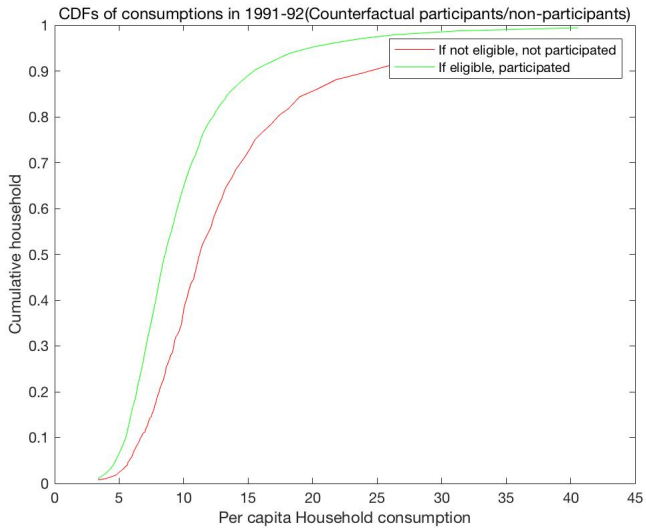
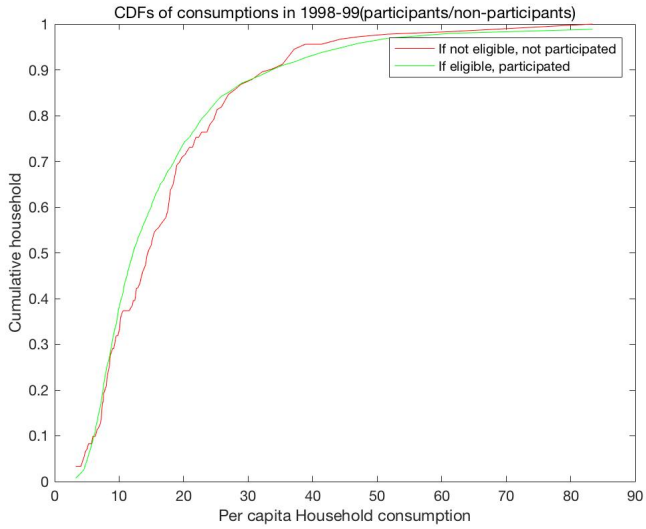


Figure 4: Counterfactual CDFs of consumption with and without microfinance in 1998/99



The empirical CDFs show that the counterfactual CDF of households that participate in microfinance programs lies below the CDFs of households that do not participate in years 1991/92. This is consistent with the findings in the previous section. Even after controlling for the self-selection bias, the microfinance programs seems to have no positive influence on consumption and the counterfactual non-participants even enjoy higher consumptions all over the consumption distribution. However, the relationship changes in 1998/99 so that the cumulative distribution functions cross, and the CDF of counterfactual participants lies below the CDF of non-participants only at the bottom 10% and the top 12% of the population. This is also shown by the formal stochastic dominance test results. Under the null hypothesis that CDF of counterfactual non-participants stochastically dominates that of participants, I could not reject the null hypothesis in both the FOSD or SOSD sense in years 1991/92 and also in 1998/99. On the other hand, I could reject the reversed tests of FOSD and SOSD in 1991/92. In 1998/99, we can reject the reversed test for SOSD but cannot reject the test for FOSD. The results indicate that there is statiscal evidence of non-participants' consumption stochastically dominating participants' consumption in 1991/92, but in 1998/99 there is no FOSD relationship in either way or another, but we can reject the SOSD of counterfactual participants over non-participants.

Comparing counterfactual distributions of consumptions with and without microfinance treatment changes the results from the previous section's preliminary stochastic dominance tests. The postive effects of microfinance

programs on consumption disappear in years 1998/99, but I could find some evidence that microfinance alleviates consumption poverty at the left and right tail of distribution when it is maintained for some extended period even after controlling for the unobserved self-selection bias. This indicates that for people in the moderate consumption level, the positive effect of microfinance on poverty can be attributed to the self-selection effect. However, for the extreme poor and the rich, the effect of microfinance programs still remains after controlling the self-selection. Still, the stochastic dominance of participants over non-participants disappears.

5 Poverty Indices and Stochastic Dominance Tests

As I have mentioned above, most previous literatures on microfinance measure the impact of microfinance on poverty by using headcount ratio or normalized poverty deficit. The definition of headcount ratio is $H = \int_0^z f(x)dx = F(z)$, where F indicates income or consumption distribution and z indicates the poverty line. Headcount ratio measure the percentage of total population who are under poverty. This index is insensitive to the distribution among the poor, in that the reduction of income or consumption for those who are below the poverty line does not affect the index. Also, the transfer of income from a person below the poverty line to anyone who is richer doesn't affect the headcount ratio as well. The axiom that reduction of income for people

below the poverty line should worsen the poverty index is called monotonicity axiom, and that transfer from the poor to the rich should also worsen the poverty index is called transfer axiom by Amartya Sen (1976).

Normalized poverty deficit measures the aggregate gap of incomes from the poverty line for those who are under the poverty line. It is measured as $D = \int_0^z (1 - \frac{x}{z}) f(x)dx = \frac{1}{z} \int_0^z (z - x) f(x)dx$. This measure satisfies the monotonicity axiom, but violates the transfer axiom. (n other words, the redistribution between those who are under the poverty line does not change the normalized poverty deficit. Therefore, these two poverty indices are inappropriate in measuring extreme poverty since they omit very important information.

We need a index which gives weight to the income gaps to capture extreme poverty better, and Foster-Greer-Thorbecke poverty indices is the simplest way to do that. The FGT index is defined as $P_\alpha = \int_0^z (1 - \frac{x}{z})^\alpha f(x)dx$, where α indicates how much weight we will give to the income gap. We can see that when $\alpha = 0$, it is equivalent with the headcount ratio and it is the normalized poverty deficit when $\alpha = 1$. The FGT index satisfies the monotonicity and transfer axioms when $\alpha \geq 2$.

The comparison of the FGT poverty indices is very similar to that of

stochastic dominance tests. For stochastic dominance tests, we defined

$$
\begin{aligned}
F_0(x) &= f(x) \\
F_1(x) &= \int_0^x F_0(t)dt \\
F_s(x) &= \int_0^x F_{s-1}(t)dt = \frac{1}{(s-1)!}\int_0^x (x-t)^{s-1} f(t)dt, s \geq 2
\end{aligned}
$$

The only difference between FGT poverty indices and stochastic dominance tests is that FGT poverty indices is divided by z. which is the poverty level. So by conducting stochastic dominance tests, we can figure out whether there has been a decrease in FGT poverty indices. First order and second order stochastic dominance indicates the decrease in headcount ratio and normalized normalized poverty deficit respectively, and FGT poverty indices of higher α can be linked with higher order stochastic dominance. While FOSD and SOSD surely leads to lower FGT poverty indices, we should note that lower FGT poverty does not imply the stochastic dominance relationships. Since stochastic dominance relationship exists only when the inquality holds for all levels of consumption, FGT poverty index which is an aggregation over the whole population does not preserve the whole information in the stochastic dominance relationship.

In this section, I apply the 3 poverty indices in our data to show that if the choice of poverty indices shows varying effect of microfinance on poverty. To compute poverty indices, it is necessary to select the poverty line. The poverty indices are sensitive in selecting the poverty line, and can have misleading outcomes shen inappropriate poverty line is selected. Here, I use a

dollar-a-day line suggested by Ravallion et al. (1991). Since the data covers the period from 1992 to 1999, I use the updated line in 1992, which is $1.08 per day using 1993 PPPs.

Table 5: Comparison of poverty indices of the whole population and the compliers

		Headcount ratio	Normalized poverty deficit	FGT index ($\alpha = 2$)
Whole population	participants	0.9191	12.8976	98.8058
	non-participants	0.9411	13.2068	101.1919
Compliers	participants	0.9329	13.2564	102.5243
	non-participants	0.8723	10.8837	76.4357

When we consider the whole population, all the three different poverty indices show that microfinance program participants exhibit less poverty than non-participants. When we consider the counterfactual consumption of the compliers, FGT poverty indices indicate that there was a increase in consumption poverty as a whole. Therefore, even the mean-level improvement of consumption poverty is entirely lost after the control of non-random participation.

6 Conclusion

Evaluating impacts of programs is necessary, but has many hardships. To get over these hardships, this study uses panel survey data which helps to capture the net effect of the microfinance program by getting rid of the problems that rise from endogeneities. Firstly, I have conducted the fixed-effects regression that eliminates the individual-level and village-level heterogeneities. It is shown that microfiance loans have positive, but minute effect on increasing poverty while other factors of microfinance programs such as borrower being female had significantly large effect on increasing consumptions.

This paper also conducts stochastic dominance tests before and after controlling for the selection bias. The preliminary analysis before controlling the selection bias indicates the stochastic dominance of microfinance non-participants over participants in years 1991/92 while the relationship completely reverses in 1998/99. After controlling the selection bias, the stochastic dominance of non-participants over participants still remains in 1991/92, but the reversed SD relationship in 1998/99 disappears and the CDFs cross twice at approximately 10% and 88% region of the distribution. This implies that microfinance programs have different effects depending on the duration of the programs. When the microfinance programs were introduced just before, in 1991/92, there seems to have no effect of microfinance and the program participants even exhibit lower consumptions. As time passes, this relationship changes and the consumption of microfinance participants becomes larger than that of non-participants only for the very poor (bottom 10%) and for

the relatively rich (top 12%). On the other region of the distribution function, the non-participants show higher consumption level.

It is resounding to find evidence that taking account of the endogeneities weakens or eliminates the positive effects of microfinance programs on consumption poverty. The SD relationship that existed in the preliminary analysis disappears after controlling for the non-random program participation. This result may be due to the individual heterogeneities between program participants and non-participants. Those who participated in microfinance programs might have better entrepreneurial abilities than those who didn't, so they would have been able to consume more even if they did not participate in microfinance programs. If this was the case, effects of microfinance programs would be overestimated before controlling for these self-selection effects.

We cannot say that the microfinance programs have increased participants' consumption all over the distribution, and the consumption poverty in terms of FGT poverty indices also does not decrease with microfinance programs as we have seen in the poverty indices analysis in section 5. The effects of microfinance is complex and it does not increase consumption for everyone, but it seems that if the microfinance program is sustained long enough, it increases the consumption level for the very poor and the rich.

References

1. Abhijit Banergee, Esther Duflo, Rachel Glennerster, and Cynthia Kinnan, *The Miracle of Microfinance? Evidence from a Randomized Evaluation*, American Economic Journal: Applied Economics, 7 (1): 22-53, 2014.

2. Alberto Abadie, *Bootstrap Tests for Distributional Treatment Effects in Instrumental Variable Models*, Journal of the American Statistical Association, 97:457, 284-292, 2002.

3. Amartya Sen, *Poverty: An Ordinal Approach to Measurement*, Econometrica, Vol. 44, No. 2, 219-231, 1976.

4. Anthony B. Atkinson, *On the Measurement of Inequality*, Journal of Economic Theory, Vol. 2, 244-263, 1970.

5. Anthony B. Atkinson, *On the Measurement of Poverty*, Econometrica, Vol. 55, No. 4, 749-764, 1987.

6. Buhong Zheng, *Aggregate Poverty Measures*, Journal of Economic Surveys, Vol. 11, Issue 5, 123-162, 2002.

7. Garry F. Barrett, Stephen G. Donald, *Consistent Tests for Stochastic Dominance*, Econometrica, Vol. 71, Issue 1, 71-104, 2003.

8. Gordon Anderson, *Nonparametric Tests of Stochastic Dominance in Income Distributions*, Econometrica, Vol. 64, No. 5, 1183-1193, 1996.

9. Hulme David, Paul Mosley, *Finance against Poverty*, Vol. 2. London: Routledge, 1997.

10. James Foster, Joel Greer and Erik Thorbecke, *A Class of Eecomposable Poverty Measures*, Econometrica, Vol. 52, No. 3, 761-766, 1984.

11. James Foster, Joel Greer and Erik Thorbecke, *The Foster-Greer-Thorbecke Poverty Measures: 25 Years Later*, The Journal of Economic Inequality, Vol. 8, Issue 4, 491-524, 2010.

12. Manuela Angelucci, Dean Karlan, and Jonathan Zinman, *Win Some Lose Some? Evidence from a Randomized Microcredit Placement Experiment by Compartamos Banco*, NBER Working Paper No. 19119, 2013.

13. Martin Ravallion, Gaurav Datt, and Dominique van de Walle *Quantifying Absolute Poverty in the Developing World*, The Review of Income and Wealth, Vol. 37, Issue 4, 345-361, 1991.

14. Oliver Linton, Esfandiar Maasoumi, and Yoon-Jae Whang, *Consistent Testing for Stochastic Dominance under General Sampling Schemes*, The Review of Economic Studies, Vol. 72, Issue 3, 735–765, 2005.

15. Russell Davidson, Jean-Yves Duclos, *Statistical Inference for Stochastic Dominance and for the Measurement of Poverty and Inequality*, Econometrica, Vol. 68, Issue 6, 1435-1464, 2000.

16. Shahidur R. Khandker, *Microfinance and Poverty: Evidence Using Panel Data from Bangladesh*, The World Bank Economic Review, Vol. 19, Issue 2, 263–286, 2005.

요약 (국문초록)

본 논문은 소액금융이 소비 빈곤에 미치는 영향을 방글라데시의 패널 데이터를 이용하여 분석한다. 이전 연구들에서는 소액금융의 효과가 빈곤자 비율 등의 전통적인 빈곤 지수를 이용해 평균 수준에서만 분석되어 왔다. 그러나, 소액금융이 서로 다른 사회경제적 위치의 사람들에게 미치는 영향을 파악하기 위해서는 분포적 접근이 필요하다. 따라서, 본 논문에서는 고정효과 모형을 이용하여 소액금융이 평균적으로 소비 빈곤에 미치는 효과를 분석한 후 확률적 지배관계를 도입해 전 분포에 걸친 소액금융의 효과를 알아본다. 고정효과 모형에서는 소액금융 참여가 소비 빈곤을 약간 감소시킨다는 결과를 얻었으나, 소액금융 프로그램 참여에서 발생할 수 있는 자기선택 편의를 제거하고 난 뒤의 확률적 지배관계 분석 결과 소액금융 참여가 빈곤을 감소시킨다는 근거를 찾을 수 없다. 또한, 전통적 빈곤 지수를 이용한 평균 수준에서의 빈곤 역시 감소하지 않는 것으로 나타났다.

주요어: 소액금융, 빈곤, 빈곤지수, 고정효과 모형, 확률적 지배, 분포상의 처치효과, 역사실적 분포

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