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Abstract

This paper tests the hypothesis that microfinance reduces poverty at macro level using the cross-country data in 2007. The results of econometric estimation for poverty head count ratio show, taking account of the endogeneity associated with loans from microfinance institutions (MFIs), that microfinance loans significantly reduce poverty. Thus, a country with higher MFI's gross loan portfolio tends to have lower poverty incidence after controlling the other factors influencing poverty. We also found that poverty reducing effect tends to be larger in Sub Saharan Africa (SSA) as suggested by the negative and significant coefficient estimate of the SSA dummy and gross loan portfolio. From a policy perspective, our results would justify increase in investment from development finance institutions and governments of developing countries into microfinance loans as a means of poverty reduction.

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Analysis of Poverty Reducing Effects of Microfinance from a Macro Perspective: Evidence from Cross-Country Data

I. Introduction

Most of the recent studies of the impact of microfinance on poverty or income have relied on micro-level evidence based on household data or entrepreneurial data (e.g. Hulme and Mosley, 1996, Mosley, 2001, Khandker, 2005, Imai et al., 2010, Azam and Imai, 2010). Due to the scarcity of the reliable macro data on microfinance, macro-level studies of the impact of microfinance on poverty are rather limited. However, there are a few recent works that investigate the relationship between the macro economy and microfinance activities and/or performance, such as Ahlin et al. (2010), Ahlin and Lin (2006) and Kai and Hamori (2009). The thrust of these studies is either to examine the environmental context in which microfinance operates, or investigate the potential effect of microfinance on key macroeconomic variables, such as gross domestic product or inequality. The findings of a significant relationship between operations of microfinance institutions (MFIs) and the macro economy corroborates the recent evidence based on household data sets which posits that microfinance has a poverty reducing effect (e.g. Khandker, 2005, Imai et al., 2010).

The challenges for empirical macro studies of microfinance include (a) identifying an appropriate measure of microfinance activities, in terms of 'availability' or 'intensity'; (b) identifying the effects of 'performance', distinguished from 'presence' and 'scale' of microfinance on macro indicators; and (c) examining the robustness of coefficient estimates related to microfinance. Building on the small but emerging literature on analysing the impacts of microfinance from a macro perspective, the present study aims to show empirical evidence of the relationship between MFI's gross loan portfolio and poverty head count. The results would be useful for development partners as they will provide an insight into the effects of MFI loans on poverty. Another aim is to further incite the need for macro-level studies of microfinance in developing countries. These objectives are important in view of the increasingly significant role of microfinance as a means of alleviating poverty in developing countries, which has been widely recognised among development partners.

This paper statistically tests the hypothesis that microfinance reduces poverty using cross-country data. More specifically, we examine whether a country with higher MFI's gross loan portfolio has lower poverty incidence after controlling the factors influencing poverty and taking account of the endogeneity associated with MFI's gross loan portfolio. We include regional dummies in the control variables and explore differential effect of gross loan portfolio on poverty across different regions. This will facilitate an examination of whether variations in gross loan portfolio in different regions would affect poverty levels. From a policy perspective, this is important for development finance institutions and microfinance investment vehicles to reassess their microfinance loan portfolios, that is, on-lending funds and other portfolios of microfinance.

The rest of the paper is organized as follows. The next section summarizes the recent evidence of the effects of microfinance on poverty in developing countries. Section III provides a brief explanation of the data which the present study draws upon. Econometric specifications are discussed in Section IV. The main results are presented in Section V. The final section offers some concluding observations.

II. Recent Studies of Poverty and Microfinance

As a background of our study, we will first summarise the recent evidence of micro-level studies which assessed the impacts of microfinance on poverty in India and Bangladesh.

Imai et al. (2010) analysed the impact of access to MFIs and MFI loans on household poverty in India drawing upon a national-level cross-sectional household data set in India in 2000 conducted by EDA rural systems and showed that access to MFIs and MFI loans significantly reduced poverty. They used the Indexed Based Ranking (IBR) Indicator which reflects multi-dimensional aspects of poverty, covering aspects of food security, assets, health, employment and agricultural activities. [1] To address the issue of endogeneity, the treatment effects model, a version of the Heckman sample selection model, Tobit model and the propensity score matching (PSM) model were used to estimate poverty-reducing effects of access to MFIs and loans used for productive purposes, such as investment in agriculture or non-farm businesses. They found that for households in rural areas, a larger poverty reducing effect of MFIs is observed when access to MFIs is defined as taking loans from MFIs for productive purposes than in the case of simply having access to MFIs. In urban areas, on the contrary, simple access to MFIs has larger average poverty-reducing effects than taking loans from MFIs for productive purposes. That is, clients' intended use of loans is important in determining poverty reduction outcomes. This implies that it would be important for development partners to develop a consistent framework to monitor the usage of loan with adequate flexibility to capture different levels of participating nature of the households.

Imai and Azam (2010) have recently analysed the effects of microfinance on poverty

[1] It is noted that Imai et al. (2010) did not define poverty in terms of income or consumption because of the lack of data.

drawing upon the panel data of households in Bangladesh. The data are based on the four-round panel survey which was carried out by the Bangladesh Institute of Development Studies (BIDS) for Bangladesh Rural Employment Support Foundation (PKSF, Bengali acronym) with funding from World Bank. All four rounds of the survey were conducted during the December-February period in 1997-98, 1998-99, 1999-2000, and 2004-05. It covered over 3000 households in each round distributed evenly throughout Bangladesh so as to obtain a nationally representative data set for the evaluation of microfinance programmes in the country. A sample of villages under each of the selected MFI was drawn through stratified random sampling and control groups were selected from the neighbouring villages without any MFI. Imai and Azam (2010) have applied treatment effects model and propensity score matching where (a) 'the treatment' is either whether a household had access to loans from MFI for general purposes or whether a household obtained loans from MFI for productive purposes and (b) a dependent variable is per capita household income. It is found by Imai and Azam that simple access of a household to MFI did not significantly increase per capita household income, while loans for productive purposes did, which is consistent with Imai et al.'s (2010) finding on households in rural India.

In sum, microfinance, in particular, the loans for productive purposes, reduced poverty significantly in both India and Bangladesh.[2] Our finding based on the cross-county data supports these conclusions as we will see in the subsequent sections.

[2] See Imai et al. (2010) and Imai and Azam (2010) for other evidence of the relationship between microfinance and poverty at household levels.

III. Data

The present study analyses the effect of microfinance operations – volume/scale of activities (not performance) on poverty incidence using cross country data covering 99 countries in developing countries[3] for 2007. This is based on the data generated by Microfinance Information Exchange (2010) or MIX data and the World Development Indicators 2010 (World Bank, 2010). While poverty measures at the country level have been widely used among academics and practitioners, a measure of microfinance operations (volume/scale) in a country is yet to gain momentum. In terms of poverty, this paper opts for the head count ratio based on the popular Foster-Greer-Thorbecke (Foster et al., 1984) as a dependent variable. Our choice of the head count poverty index is informed by its easy accessibility and interpretability relative to depth and severity of poverty measures.

We have tried three indicators, namely, number of microfinance institutions (MFIs), number of active borrowers of MFIs and gross loan portfolio of MFIs, for the measure of microfinance activities in a country. While all these measures possess varied degrees of limitations in capturing intensity and distributional features of microfinance activities in a country, we use gross loan portfolio (GLP) given that it measures the actual funds which have been disbursed to households. Gross loan portfolio is likely to have a more direct income-enhancing or poverty-reducing effect[4] than the number of MFIs and the number of active borrowers of MFIs. The number of MFIs or active borrowers is used either as a weighting factor or one of the explanatory variables.

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[3] See Appendix 1 for the list of the countries.

[4] It is noted that misuse (fungibility) of loans might restrict the poverty-reducing effect. Here we assume that the amount of misused loans is negligible at macro levels. However, micro-level evidence suggests that loans are often used for non-productive purposes (e.g. Imai et al., 2010) and the future research should investigate the issue of misuse in details.

We use the standardized median of GLP generated by the Microfinance Information Exchange (MIX) as a benchmark indicator. The standardization of raw data facilitates meaningful comparison of benchmark indicators (MIX, 2010). Other variables in the poverty equation include gross domestic product (GDP), GDP deflator, access to finance, number of active borrowers of MFIs and regional dummies.[5]

IV. Econometric Model

In this paper, our multivariate analysis is based on the cross sectional data for 2007 not only because extensive and reliable historical data on microfinance do not exist [6] but also because the data on poverty head count ratio are available in only limited years, which would make the country panel data of poverty highly unbalanced.

We apply both OLS and IV (Instrumental Variable) model or 2SLS (Two Stage Least Squares) to estimate the effect of gross loan portfolio of microfinance on poverty head count ratio. 2SLS involves two stages: gross loan portfolio of microfinance is estimated by an instrumental variable and other covariates in the first stage and in the second poverty head count ratio is estimated by the predicted gross loan portfolio and covariates. The use of IV is necessary because gross loan portfolio of microfinance is likely to be endogenous in the poverty equation. Here the endogeneity is associated with the bi-casual relationship between gross loan portfolio and poverty levels in a country. This reverse causality from poverty incidence to gross loan portfolio may arise, for example, if poverty-oriented development partners and governments provide more funds to MFIs located in poorer countries. With the usual data constraint in finding a valid instrument

[5] See Table 1 for descriptive statistics of these variables. These will be discussed in Section IV.
[6] MIX data date back to 1994, but not until 2002 most MFIs were not keen on submitting their records for public use.

that satisfies 'an exclusion restriction', that is, correlates with gross loan portfolio but not poverty, this papers uses lag of five-years average of gross loan portfolio weighted by the number of MFIs for every country[7]. The unit of analysis for the econometric exercise is the country.

Equations (1) and (2) below describe respectively the structural and reduced form of least squares used in estimating the relationship between gross loan portfolio and poverty incidence.

$$
\begin{aligned}
Pov_i = \beta_0 + \beta_1 GLP_i + \beta_2 GDP_i + \beta_3 GDPDEF_i + \beta_4 NoAB_i + \beta_5 Acc.Fin._i \\
+ .\beta_5 Acc.Fin._i + .\beta_6 DomCred_i + \beta_7 NoAB * GLP \\
\beta_8 \mathbf{REG}_i + \beta_9 \mathbf{REG} * \mathbf{GLP}_i + u_i \qquad (1)
\end{aligned}
$$

$$
GLP_i = \pi_0 + \pi_1 GLPMF_i + \pi_2 MFIs_i + \pi_3 \mathbf{X}_i + \upsilon_i \qquad (2)
$$

where 'Pov' indicates poverty head count ratio; 'GLP' represents gross loan portfolio; 'GDP' symbolizes gross domestic product at constant USD prices; 'GDPDEF' stands for GDP deflator; 'NoAB' is the acronym for number of active borrowers of microfinance loans; 'Acc.Fin' represents access to finance (composite index measuring availability, affordability and eligibility of access to finance in a country based on Honohan (2007)); 'Domcred' indicates domestic credit of banks as a proportion of GDP; 'NoAB*GLP' is the interaction term between number of active borrowers and gross loan portfolio of MFIs; 'REG' is a vector of regional dummies with Latin America and Caribbean being the reference region; 'REG*GLP is the vector of interaction between regional dummies and gross loan portfolio. Equation (2) is the reduced form, which tests the presence of

[7] This index passes the statistical validity of a valid instrument as it shows a high correlation with gross loan portfolio and a low correlation with poverty head count ratio (with the coefficient of correlation 0.8 for the former and 0.1 for the latter respectively).

endogeneity and suitability of our instruments. ‘GLPMF’ is the weighted five-year average lag of gross loan portfolio with number of MFIs for every country; ‘MFIs’ is the number of MFIs in the country for the current year (2007) and **X** is the vector of all the other explanatory variables considered in equation (1). The respective independently and identically distributed (iid) error terms for the two equations are denoted by ‘u’ and ‘υ’.

V. Results

Figures 1 to 3 below, describe the patterns and trends of size and outreach of the microfinance industry using gross loan portfolio, number of MFIs and active borrowers. Overall, the compound growth rate of the median gross loan portfolio increases for all regions over the period 2005 to 2009. However, there are variations (steep and gentle) in the year-by-year upward slopes, while in one instance (Eastern Europe and Central Asia), a downward trend is observed. In particular, the slope for 2007 to 2008 is either gently increasing or sloping downwards. An interpretation of the trend over this period will need to take cognizance of the potential adverse effect of the global financial crisis on the microfinance industry.

Until 2007, the largest MFIs were located in Latin America and the Caribbean (LAC). However, in 2008 MFIs in Middle East and North Africa (MENA) experienced a sharp increase in their gross loan portfolio. Comparison of the patterns and trends of gross loan portfolio with the greater and sharp increase in number of active borrowers in South Asia (Figure 2) would trigger a number of questions, especially when using either of these indicators as a measure of microfinance operations in a country. Two reasons can be respectively surmised for the greater and sharp increase in South Asia’s number of active borrowers. Firstly, one can argue that by virtue of population size of countries in this region, it is by no means surprising that MFIs are able to reach out to more clients (scale of outreach). Secondly, differences in the mission of MFIs as a result of country (regional) level influences can account for the variation in the scale of outreach (number of clients). Thus, MFI's with outreach focus (poverty-reducing) are likely to reach out to more clients.

Number of MFIs for the different regions and over time (Figure 3), presents another challenge in choosing an index to measure microfinance operations in country. Figure 3 shows that LAC consistently (since 2005) have the highest number of MFIs in spite of its relatively smaller number of active borrowers compared to South Asia (SA) and MENA.

Figure 1: Trends and Patterns of Gross Loan Portfolio

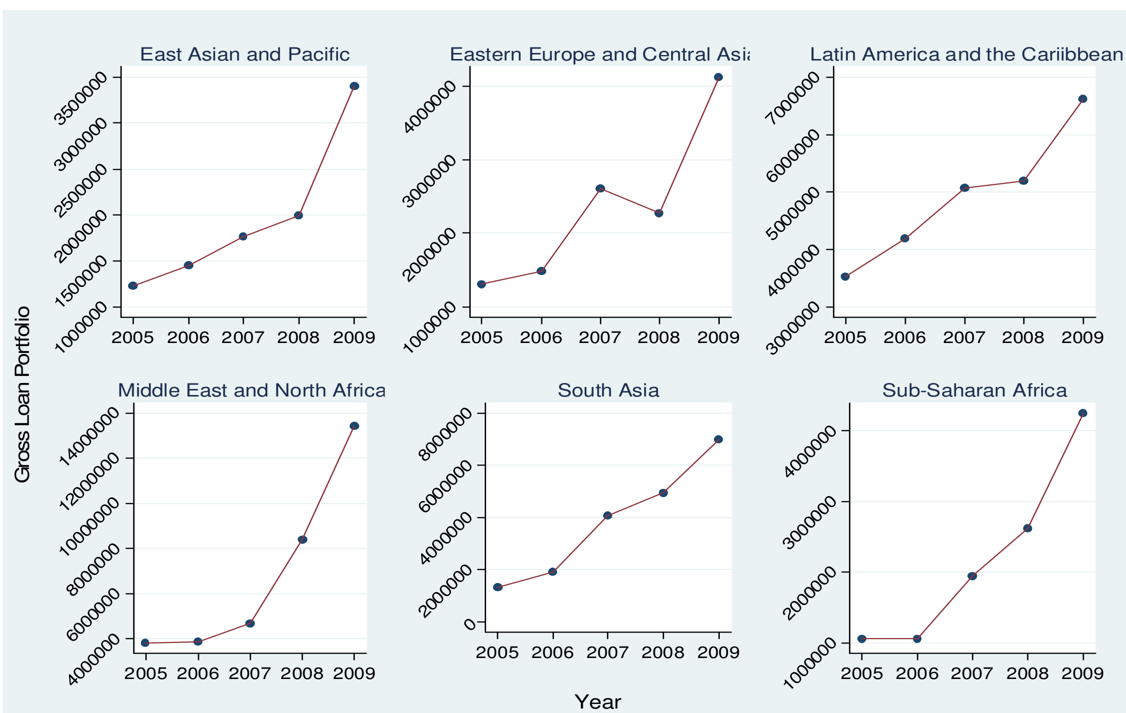

Figure 2: Trends and Patterns of Number of Active Borrower

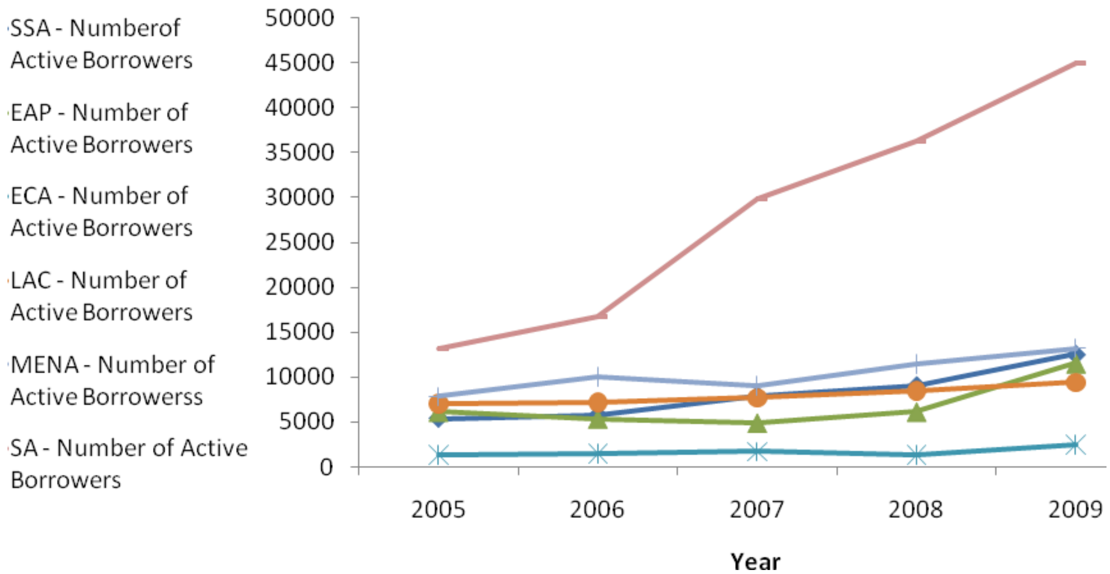

Figure 3: Trends and Patterns of Number MFIs

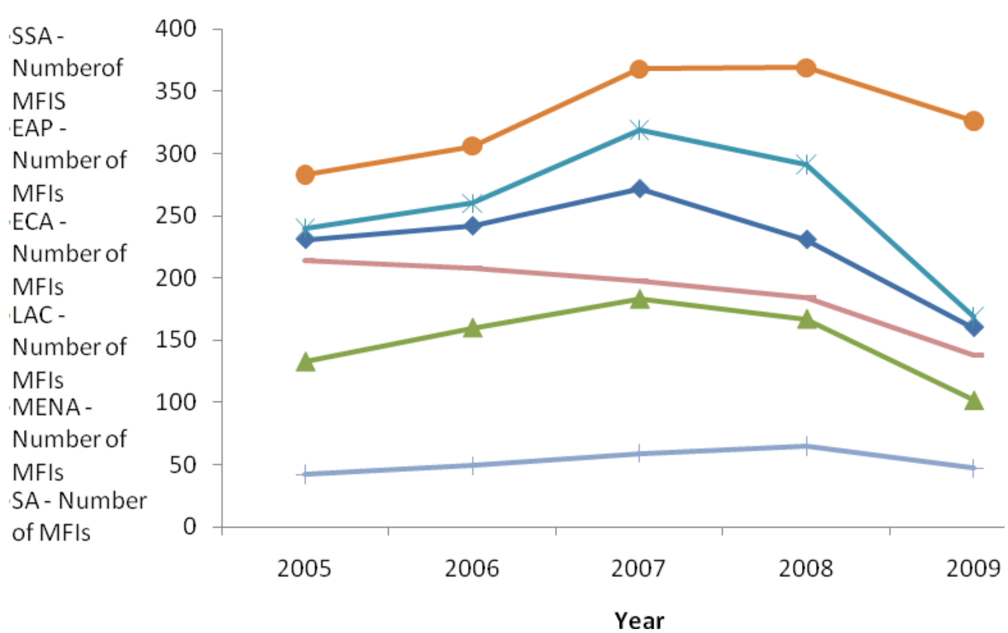

Table 1 provides a summary statistics of the variables used for the multivariate analysis. We report both mean and median of each variable for the respective regions. The rationale for reporting median alongside the mean is to provide a further justification for the choice of median for the descriptive statistics and the need to use the logarithmic form of variables with high standard deviations (skewness) for the multivariate analysis. In view of the heterogeneity of the size of MFIs (gross loan portfolio); outreach (number of active borrowers) and a nation's output (GDP), it is always prudent to observe the distribution of the data. Table 1 indicates that the median in some instances is about either a hundredth (East Asia and the Pacific (EAP)) or a tenth (MENA) of the mean. This suggests that the raw data for the mean are likely to be affected by extreme values.

From the perspective of both number of active borrowers and MFIs, microfinance activities in SA countries is more intense than in the other regions. At the lower end, MFI activities in Sub-Saharan Africa (SSA) countries tend to show the least values for gross loan portfolio and the number of active borrowers indicating a less intense level of microfinance operations relative to the other regions. As observed from the trends (Figures 1–3), variations in these indicators over time and across different regions suggest the need to develop a meaningful index that pulls together all three variables.

In terms of the macro indicators, SSA, as expected, is the poorest region irrespective of the variable in question. However, in terms of the least 'worse off' region,[8] MENA, records the lowest poverty incidence while EAP show the highest output (GDP). In the context of the study's focus, we include a variable to capture financial deepening in a

[8] Most of the countries used in the study are either transitional or developing countries. This is because MFIs mostly evolve in countries with a high level of deprivation (mainly access to finance).

country. The variable ‘access to finance’ is based on the data of the proportion of the population in a country who have access to financial services at their disposal, affordable to them, and are eligible to take-up a financial product (Honahan, 2007). This kind of composite indicator is more suitable than other variables, such as domestic credit provided by the banking sector as a proportion of GDP, because access to finance should be redefined based on availability, continuity, flexibility and convenience following the financial inclusion literature (Claessens, 2006). Thus, since most of the available financial deepening indicators are inclined to the services offered by formal financial institutions, it is counterintuitive to use such indicators for microfinance studies. We demonstrate this by ranking regions based on domestic credit and access to finance. The rank of a region for the two variables confirms the varied perspectives of the indicators. With the exception of SSA, that ranks worse (last) in both indicators, all other regions show significant differences in their ranks for the two variables. For instance, while MENA ranks the first with domestic credit, it turns out to be the second from the bottom in terms of access to finance.

Table 1: Summary Statistics of Variables (2007)

Region	Statistic	Gross Loan Portfolio	Number of Active Borrowers	Number of MFIS	Domestic Credit/GDP	Poverty Incidence	Gini	Access to Finance	GDP(constant USD)	GDP Deflator
EAP	***Mean***	316833959	857546	15	50.94	30.93	40.33	0.30	3.30E+11	448.43
	Median	6076436	12084	5	40.6	36.50	41.5	0.27	5.26E+10	201.18
ECA	***Mean***	292101715	89369	10	39.5	35.59	33.7	0.32	6.67E+10	341.11
	Median	199041862	68506	6	37.6	31.5	33.55	0.23	1.76E+10	194.88
LAC	***Mean***	769656782	631552	19	45.41	40.85	51.83	0.32	1.33E+11	352.91
	Median	305390729	252551	15	41.56	42	52.3	0.29	2.28E+10	207.28
MENA	***Mean***	101265159	225422	5	76.65	21.3	37.84	0.26	3.87E+10	361.68
	Median	14512016	18909	5	80.53	21.3	37.7	0.23	2.42E+10	175.05
SA	***Mean***	317539124	2142664	29	43.8	37.05	37.48	0.34	1.95E+11	148.22
	Median	121747636	506134	24	47.55	38.9	36.8	0.32	6.96E+10	147.47
SSA	***Mean***	91675681	196864	7	21.3	52.59	43.28	0.22	1.38E+10	35563.13

	Median	17452634	65922	7	13.52	52	43.1	0.21	3.98E+09	223.41
Total	***Mean***	307941986	447935	12	40.03	40.93	41.83	0.28	9.38E+10	11828.69

The results of multivariate regressions are presented in Table 2. With the view to examining the hypothesis on the inverse relationship between gross loan portfolio and poverty incidence and investigating differential effects of gross loan portfolio for the different regions, six different cases of estimations are presented in Table 2 where OLS is applied for columns (1)-(4) and (6) and IV for column (5). All the estimations are robust (correct for potential heteroskedasticity) with the exception of the last two columns of Table 2.

Table 2: Model Comparison of the Estimation Results between Poverty incidence and Gross Loan Portfolio of MFIs
Dependent variable – Poverty Head Count Ratio

Explanatory Variables	**OLS** Without logs, regional effects and interaction terms (1)	**OLS** Without regional effects and interaction terms (2)	**OLS** With NoAB/GLP Interaction and regional dummies (3)	**OLS** With interaction terms (4)	**IV** (Instrumental variable) regression (5)	**OLS** the same set of variables as (5) (6)
GLP (mfi)	**0.00*1**					
	(-2.15)					
LOG.GLP(mfi)		**-2.39^{+}**	**-10.61****	**-10.97^{+}**	**-23.35***	**-10.61***
		(-1.78)	**(-3.20)**	**(-1.94)**	**(-2.55)**	**(-2.56)**
NoAB (mfi)	0.00					
	(-0.43)					
LOG.NOAB (mfi)		3.37**	-3.21	-7.18	-16.24^{+}	-3.21
		(-2.62)	(-0.82)	(-1.41)	(-1.61)	(-0.56)
ACCESS FIN. (mfi)	-64.52**	-30.89*	-27.40*	-30.22**	-24.72*	-27.40*
	(-6.53)	(-2.37)	(-2.31)	(-2.71)	(-1.97)	(-2.17)
GDP DEF.	-0.00**	-0.00**	-0.00**	-0.00**	0.00	0.00
	(-3.42)	(-5.16)	(-5.06)	(-4.05)	(-1.16)	(-1.21)
GDP	0.00					
	(-0.76)					
LOG.GDP		-4.16**	-3.57**	-2.40^{+}	-4.52**	-3.57**
		(-3.54)	(-3.24)	(-1.76)	(-3.37)	(-2.94)
*NoAB*GLP(mfi)*			0.51*	0.67*	1.40*	0.51^{+}
			(-2.27)	(-2.05)	(-2.14)	(-1.60)
MENA			-24.91**	29.29	-26.59**	-24.91**
			(-4.97)	(-0.78)	(-3.96)	(-3.70)
SSA			0.31	69.00^{+}	-1.36	0.31
			(-0.07)	(-1.69)	(-0.29)	-0.07
ECA			-1.55	-47.78	2.07	-1.55
			(-0.35)	(-1.03)	(-0.41)	(-0.35)
EAP			-18.33**	-15.46	-23.51**	-18.33**
			(-4.88)	(-0.50)	(-3.36)	(-2.93)

SA			-13.95*	34.65	-19.39*	-13.95^{+}
			(-2.45)	(-0.85)	(-2.40)	(-1.89)
*MENA*GLP(mfi)*				-2.91		
				(-1.47)		
*SSA*GLP(mfi)*				-3.71^{+}		
				(-1.73)		
*ECA*GLP(mfi)*				2.55		
				(-1.01)		
*EAP*GLP(mfi)*				-0.11		
				(-0.07)		
*SA*GLP(mfi)*				-2.53		
				(-1.18)		
Constant	58.31**	152.17**	258.17**	247.55**	471.47**	258.17**
	(-15.27)	(-5.22)	(-4.52)	(-2.67)	(-3.02)	(-3.42)
Observations	78.00	78.00	78.00	78.00	78.00	78.00
R-Squared	0.32	0.42	0.58	0.63	0.52	0.58
F-Statistic	- *2	13.46	11.51	13.16	7.23	8.29

*1 ** Significant at one percent; * significant at five percent; $^{+}$ significant at 10 percent; t-values are in parenthesis
*2 In this instance, the interpretation of F-statistic is likely to be ambiguous as a result of the model specification STATA fails to report the F-statistic.

Column (1) estimates the poverty reducing effect using the anti-logarithmic form of the data. The model's fitness results points to a specification problem because the R-Squared is low. In spite of this limitation, we observe a negative and statistically significant relationship between gross loan portfolio and incidence of poverty, which is consistent with our hypothesis that gross loan portfolio reduces the incidence of poverty.

In column (2), we estimate the effect of MFI loans on poverty incidence based on the logarithmic forms of gross loan portfolio together with gross domestic product and number of active borrowers and other control variables. Log of gross loan portfolio of MFI is negative and significant at 10% level. This case yields expected results for all the other right hand side variables but GDP deflator. Access to finance, GDP and number of active borrowers of MFI are negative and statistically significant.

Columns (3) and (4) explore the potential effect of regional dummies as well as regional differential effect on incidence of poverty. Inclusion of regional dummies in the poverty equation reveals that MENA, EAP and SA dummies with reference to LAC, are negative and highly significant. Also, the coefficient of gross loan portfolio tends to be greater with a higher level of statistical significance. The interacted effect of number of active borrowers of MFI and gross MFI loan portfolio is explored in column (3) by including an interaction term. The coefficient estimate of the interaction term is negative and significant, implying that the country with higher amount of MFI loans as well as a larger number of borrowers tends to have lower poverty incidence. We also examine the regional difference of poverty reducing effects of MFI loans by including the interaction of regional dummies and gross loan portfolio. The results show that the interaction of gross loan portfolio (GLP) with SSA (Sub-Sahara Africa) turned out to be negative and significant. That is, the poverty reducing effect of MFI loans tends to be larger in this region.

Column (5) presents the IV (instrumental variable) estimation with the aim of resolving the potential endogeneity of country level microfinance variables in a poverty head count equation. As discussed earlier, the endogeneity may be due to a bi-causal relationship. This is because investors who are inclined to poverty reduction might direct their financial resources to countries and regions where poverty is high. In column (6), we present the case of OLS which uses the same set variables to facilitate a decision on the trade-off between efficient and consistent estimates. Appendix 2 shows the correlation matrix which offers a statistical perspective on the validity of our instruments (number of MFIs and weighted five-year lag of gross loan portfolio) of gross loan portfolio. The Hausman test yields a chi-square of 2.93, indicating that IV should be selected over OLS. Also, the Sargan test of over identification is significant for both instruments (number of MFIs and weighted five-year lag of gross loan portfolio). Appendix 3 presents the first stage results of OLS where the instrument, weighted five-year lag of gross loan portfolio is positive and significant. This validates our use of IV model.

On the basis of the above, we still observe the expected inverse relationship between gross loan portfolio and poverty incidence after the correcting for endogeneity.

VI. Concluding Observations

This paper tests the hypothesis that microfinance reduces poverty at macro level using the cross-country data in 2007. The results of econometric estimation for poverty head count ratio show, taking account of the endogeneity associated with loans from microfinance institutions (MFIs), that microfinance loans significantly reduce poverty, that is, a country with higher MFI's gross loan portfolio tends to have lower poverty incidence after controlling the other factors influencing poverty. We also found that poverty reducing effect tends to be larger in Sub Saharan Africa (SSA) as suggested by the negative and significant coefficient estimate of the SSA dummy and gross loan portfolio. Under the recent global recession, most of the donor countries have begun to shrink their investment in microfinance after 2008. From a policy perspective, however, our results would justify increase in investment from development finance institutions and governments of developing countries into microfinance loans as a means of poverty reduction.

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APPENDICES

Appendix 1: List of Regions and Nations

No.	Regions	Nations	No.	Regions	Nations
1	East Asia and the Pacific	Cambodia	53	Middle East and North Africa	Sudan
2	East Asia and the Pacific	Papua New Guinea	54	Middle East and North Africa	Palestine
3	East Asia and the Pacific	East Timor	55	Middle East and North Africa	Yemen
4	East Asia and the Pacific	Indonesia	56	Middle East and North Africa	Egypt
5	East Asia and the Pacific	Laos	57	Middle East and North Africa	Jordan
6	East Asia and the Pacific	China, People's Republic of	58	Middle East and North Africa	Syria
7	East Asia and the Pacific	Samoa	59	Middle East and North Africa	Iraq
8	East Asia and the Pacific	Vietnam	60	Middle East and North Africa	Tunisia
9	East Asia and the Pacific	Philippines	61	Middle East and North Africa	Morocco
10	East Asia and the Pacific	Thailand	62	Middle East and North Africa	Lebanon
11	Eastern Europe and Central Asia	Uzbekistan	63	South Asia	Bangladesh
12	Eastern Europe and Central Asia	Hungary	64	South Asia	India
13	Eastern Europe and Central Asia	Georgia	65	South Asia	Nepal
14	Eastern Europe and Central Asia	Tajikistan	66	South Asia	Afghanistan
15	Eastern Europe and Central Asia	Armenia	67	South Asia	Pakistan
16	Eastern Europe and Central Asia	Montenegro	68	South Asia	Sri Lanka
17	Eastern Europe and Central Asia	Kazakhstan	69	Sub-Saharan Africa	Tanzania
18	Eastern Europe and Central Asia	Kosovo	70	Sub-Saharan Africa	Mozambique
19	Eastern Europe and Central Asia	Russia	71	Sub-Saharan Africa	Benin
20	Eastern Europe and Central Asia	Mongolia	72	Sub-Saharan Africa	Kenya
21	Eastern Europe and Central Asia	Kyrgyzstan	73	Sub-Saharan Africa	Angola
22	Eastern Europe and Central Asia	Macedonia	74	Sub-Saharan Africa	Togo
23	Eastern Europe and Central Asia	Bulgaria	75	Sub-Saharan Africa	Uganda
24	Eastern Europe and Central Asia	Serbia	76	Sub-Saharan Africa	Sierra Leone
25	Eastern Europe and Central Asia	Romania	77	Sub-Saharan Africa	Gambia, The
26	Eastern Europe and Central Asia	Turkey	78	Sub-Saharan Africa	Senegal
27	Eastern Europe and Central Asia	Moldova	79	Sub-Saharan Africa	South Africa
28	Eastern Europe and Central Asia	Ukraine	80	Sub-Saharan Africa	Guinea
29	Eastern Europe and Central Asia	Croatia	81	Sub-Saharan Africa	Cameroon
30	Eastern Europe and Central Asia	Albania	82	Sub-Saharan Africa	Mali
31	Eastern Europe and Central Asia	Bosnia and Herzegovina	83	Sub-Saharan Africa	Malawi
32	Eastern Europe and Central Asia	Poland	84	Sub-Saharan Africa	Cote d'Ivoire (Ivory Coast)
33	Eastern Europe and Central Asia	Azerbaijan	85	Sub-Saharan Africa	Burkina Faso
34	Latin America and the Caribbean	Peru	86	Sub-Saharan Africa	Swaziland
35	Latin America and the Caribbean	Brazil	87	Sub-Saharan Africa	Niger
36	Latin America and the Caribbean	Bolivia	88	Sub-Saharan Africa	Guinea-Bissau
37	Latin America and the Caribbean	Mexico	89	Sub-Saharan Africa	Congo, Republic of the
38	Latin America and the Caribbean	Costa Rica	90	Sub-Saharan Africa	Ethiopia
39	Latin America and the Caribbean	Guatemala	91	Sub-Saharan Africa	Burundi
40	Latin America and the Caribbean	Colombia	92	Sub-Saharan Africa	Nigeria
41	Latin America and the Caribbean	Trinidad and Tobago	93	Sub-Saharan Africa	Congo, Democratic Republic of the
42	Latin America and the Caribbean	Venezuela	94	Sub-Saharan Africa	Chad
43	Latin America and the Caribbean	Haiti	95	Sub-Saharan Africa	Central African Republic
44	Latin America and the Caribbean	Ecuador	96	Sub-Saharan Africa	Rwanda

45	Latin America and the Caribbean	Nicaragua	97	Sub-Saharan Africa	Ghana
46	Latin America and the Caribbean	Panama	98	Sub-Saharan Africa	Madagascar
47	Latin America and the Caribbean	Argentina	99	Sub-Saharan Africa	Zambia
48	Latin America and the Caribbean	Chile			
49	Latin America and the Caribbean	El Salvador			
50	Latin America and the Caribbean	Paraguay			
51	Latin America and the Caribbean	Honduras			
52	Latin America and the Caribbean	Dominican Republic			

Appendix 2: Correlation Matrix

	Poverty	***LOG.GDP***	***ACCESS FIN.***	***GDP DEF.***	***LOG.GLP***	***LOG. NoAB***	***LOG.GLP 5-YR***	***No. Of MFIs***
Poverty	1							
LOG.GDP	-0.5193	1						
ACCESS FIN.	-0.5605	0.5563	1					
GDP DEF.	0.4455	-0.2884	-0.2560	1				
LOG.GLP	-0.0530	0.2546	-0.0065	-0.3397	1			
LOG. NoAB	0.1112	0.2522	-0.1629	-0.1610	0.8253	1		
LOG.GLP 5-YR	-0.0791	0.3118	0.0138	-0.3529	0.8147	0.7214	1	
No. Of MFIs	0.0490	0.4225	0.0769	-0.1625	0.5039	0.5567	0.6336	1

Appendix 3: First Stage results of IV regression (Column (5) of Table 2)

	First Stage Regression Result of IV
Weighted lag of Average GLP	**0.13**** **(3.72)**
LOG.NOAB (mfi)	-0.98** (-9.48) *1
ACCESS FIN. (mfi)	0.15 -0.46
GDP DEF.	0 -0.59
LOG.GDP	-0.06+ (-1.83)
*NoAB*GLP(mfi)*	0.067** -17.35
MENA	-0.09 (-0.47)
SSA	-0.09 (-0.70)
ECA	0.25* -2.17

EAP	-0.36*
	(-2.24)
SA	-0.35+
	(-1.76)
No. of MFIs	-0.01*
	(-2.51)
Constant	14.55**
	-15.07
Observations	78
R-Squared	0.98
F-Statistic	246.49

*1 ** Significant at one percent; * significant at five percent; + significant at 10 percent; t-values are in parenthesis