Do rural microcredit borrowers fare better in reducing poverty than urban borrowers?

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Abstract

The effects of microfinance on the poverty of rural and urban borrowers using panel data are sparsely researched. This paper uses client-level balanced and unbalanced panel data from three Asian microfinance institutions (MFIs) to analyse the effects of microcredit on the poverty of urban and rural borrowers. We apply the propensity score matching (PSM) method to compare poverty levels of rural and urban borrowers, and the fixed effects (FE) model to analyse the individual changes in poverty over time. The findings of PSM suggest that the rural borrowers are poorer than their urban counterparts. This finding is consistent with the accepted belief that microcredit is preferentially extended to disadvantaged rural people as they are poorer than those living in urban areas. The results of the FE model show that rural borrowers experience stronger poverty reduction over time than their urban ones, leading to a narrowing of the rural-urban poverty gap. These results provide scientific evidence that targeting disadvantaged rural people is indeed an effective strategy for MFIs seeking higher social returns on their investments. However, despite the shrinking of the rural–urban poverty gap, the poverty differences remained persistent over time, indicating that the rural focus shall be maintained or perhaps even strengthened by MFIs and investors to further reduce poverty in rural regions. Analyses with unbalanced panel data point out two relevant issues: first, client attrition is linked to either an increase or decrease of the borrower's poverty levels at the time of exit; contradicting the general belief in the microfinance sector, that attrition relates only negatively with the outcome variable. Second, the results show that excluding dropout clients from the analysis significantly bias the estimated results.

Keywords: microfinance, scorecard, rural, panel data, propensity score matching, fixed effects

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1. Introduction

Microfinance has received much attention in development research due to its potential socio-economic benefits to poor people. Providing access to microfinance services to low-income households can positively affect them through different mechanisms: raising income-generating activities, income diversification, asset accumulation, and smoothing consumption or reducing vulnerability (Hermes & Lensink, 2011). At the macro level, access to capital reduces the income inequality within a country and boosts economic growth (Beck et al., 2007). On the flip side, financial exclusion remains a significant problem worldwide. According to the World Bank (2015), in 2014 there were still more than 2 billion adults without access to formal financial services. Low-income households are excluded from the traditional banking models due to their lack of collateral, the lack of information banks have about them (agency problem) and higher transaction costs for banks to serve them (Armendáriz & Morduch, 2010), further restraining their socioeconomic development.

Financial exclusion is more severe among poor households in rural areas (Demirguc-Kunt et al., 2015) due to the lack of a diversified economic base, the risk of crop failure or extreme weather events (Ledgerwood et al., 2013). The rural poor represent 70% of the 1.4 million people living in extreme poverty; a region of particular concern is Asia due to it having the greatest number of poor rural people (IFAD, 2011). Social investors and development institutions have become aware of this problem and have concentrated efforts in rural areas, presuming larger social returns by investing in these regions. However, there is a lack of empirical evidence about whether social returns are certainly higher when similar financial services are provided to rural borrowers compared to their urban counterparts.

This paper aims to fill this gap and contributes to microfinance literature in two different ways. First, it helps social investors and MFIs determine whether targeting low-income households in rural regions is an effective strategy that yields higher social returns. For this, the paper analyses three pro-poor credit market interventions and identifies the effects of these interventions at borrower level. As case studies, we use data from three microfinance institutions (MFIs) in Asia: ASKI (2012-2014) and RSPI (2011-2015) in the Philippines and SVCL in India (2010-2014). With all three MFIs combined, the data comprises 187,988 borrowers totalling 501,197 micro loans. The second contribution of this paper is that it analyses changes in poverty at borrower level over time. Up until now, most studies in microfinance literature (see Imai & Arun, 2008; Koloma, 2013) have compared poverty levels of rural and urban borrowers at single point in time. Use of cross-sectional data is the biggest limitation of these studies as unobserved characteristics and time effects cannot be controlled in the analysis. Berhane & Gardebroek (2011) used long-term household panel data to address this limitation; however, sample attrition markedly reduced the sample size for precisely capturing the long-term effect of microfinance. We overcame these shortcomings by exploiting readily available panel data collected by MFIs from borrowers at each loan cycle. Panel data from each MFI has a sufficient number of observations to make objective comparison of changes in urban-rural poverty over time. Another novel aspect of this study is the use of progress out of poverty index (PPI) scores to capture the multidimensional effects of credit on poverty in one single indicator. Furthermore, we shed light on the problem of attrition bias and its potential effects when analysing borrowers' data over time.

The remaining paper is organized as follows. This paper begins with a review of the literature on determinants of poverty and the PPI. This is followed by a review of impact evaluation studies using a variety of methodologies. Next, the data is described together with estimation strategies; PSM and FE were applied to the data and a sensitivity analysis was conducted. Finally, the results are discussed in the light of our research on MFIs, before drawing conclusions.

2. Literature review

2.1 Poverty determinants

Poverty is a multidimensional social phenomenon (Bhuiya et al., 2007) influenced by both macro (economic growth, political stability etc.) and micro (gender, household size etc.) parameters. Previous research on micro-determinants of poverty (Deaton & Case, 1988; Datt et al., 2000; Deaton, 2003; Geda et al., 2005; Andersson et al., 2006, Adjei et al., 2009) suggest that key factors are regional characteristics (rural/urban location, quality of governance, vulnerability to natural calamities etc.), community (availability of health services, education, infrastructure etc.) and household/individual characteristics (household size, gender of family head, number of dependents, education level, occupation etc.).

Examining poverty determinants using household data in Kenya, Geda et al (2005) shows that poverty is strongly influenced by education, household size, and sector of employment (or occupation). In addition to the aforementioned factors, Anderson et al (2006) find that geography and ethnicity of household also affects poverty. Rodriguez (2016) and Dawood et al (2008) find that occupation is also strongly connected with probability of being poor. Apata et al (2010), who examine the determinants of rural poverty in Nigeria, find that access to education reduce probability of poverty. Furthermore, Gravesteijn et al (2015) find that location (rural/urban), marital status and gender also affect the probability of being poor, among others. The study concluded that single women are less likely to be poor than married clients and rural borrowers are more likely to be poor than urban borrowers. Gang et al (2008) finds a U-shaped relationship between age and poverty, with the poverty rate increasing for age groups below 40 and decreasing for age groups 40 and above. Other studies (Gang et al., 2008, Singh et al., 2012) find that poverty increases with household size and illiteracy and decreases with education attainment, and a higher number of earning members in a household. A higher incidence of poverty is noticed among agricultural farming labourers as compared to other occupations like trading (Geda et al., 2005; Gravesteijn et al., 2015). Some of the factors influencing poverty discussed here are used for poverty analysis in this study.

2.2 Progress out of Poverty Index (PPI)

There are many ways of measuring poverty in microfinance, including income lines (Chen & Ravallion, 2008), livelihood (Sen, 1999) and well-being approaches (Gough et al., 2007). Income or consumption approaches neglect aspects like environment, access to resources and individual attributes that directly or indirectly affect poverty (Alkire & Sarwar, 2009). Due to such limitations of single dimension poverty approaches (income or consumption) in last few years, poverty measurement thinking has shifted towards multidimensional (well-being or human welfare) approaches. Some of the available tools that measure the multiple dimensions of poverty are CGAP's Poverty Assessment Tool (PAT), USAID's PATs, FINCA's Client Assessment Tool, and the PPI. Among these poverty measurement tools, PPI is most widely used by MFIs to measure their poverty outreach and track the poverty of their clients. The last decade in particular has seen a trend towards measuring income and expenditure poverty using scorecard systems such as the PPI (Chua et al., 2012; CGAP, Ford Foundation & Social Performance Taskforce, 2010; Grameen Foundation, 2014).

The PPI is an indirect poverty measurement tool based on the most recent national household income or expenditure surveys. The PPI scorecard consists of 10 questions or indicators which are: (1) strongly correlated with the household income or expenditures data from national household surveys of a given country (2) inexpensive to collect, (3) applicable to all regions in a country and (4) sensitive to poverty status changes over time. The scorecard produces a score between 0 and 100; zero indicating that a household is most likely poor. The score is converted into poverty likelihood, which gives the probability of being below a certain poverty line. The conversion from the score into a poverty likelihood is based on a calibration process, which associates each score with the share of households who have the same score and are below the poverty line in the national sample. The Indian PPI scorecard is based on the Consumer Expenditure Module of India's Socio-Economic Survey conducted by India's National Sample Survey Office, which covers 375 poverty-related indicators (Schreiner, 2016). On the other hand, the latest Philippine PPI scorecard is constructed from the 2009 Family Income and Expenditure Survey/Labor Force Survey of Philippines done by the National Statistics Office, which covers 1200 indicators (Schreiner, 2014).

The PPI scorecard has particularly gained acceptability in the microfinance industry (CGAP, Ford Foundation & Social Performance Taskforce (2010) as it is inexpensive and less prone to measurement error than conventional ways of measuring poverty (Deaton, 1997). Another advantage is that the scorecard methodology provides an accurate and contextual estimate of the depth of outreach because it can be benchmarked against the national and international poverty lines (CGAP, Ford Foundation & Social Performance Taskforce (2010). Other studies (Blauw & Franses, 2011; Larsen & Lilleor, 2013) have applied it for external impact evaluation. However, only a very few studies seem to have analysed the poverty changes of borrowers over time by using readily available PPI scores.

One challenge in capturing changes in poverty levels over time using a PPI measurement is that the score is highly sensitive to some questions and insensitive to others (Polk & Johnson, 2009). Furthermore, indicators such as cell phone ownership may only weakly explain actual household poverty changes because rapid product innovation makes these products more affordable for consumers (CGAP, Ford Foundation & Social Performance Taskforce, 2010). Desiere et al (2014) have criticized the PPI tool for its limited sensitivity to changes in poverty status resulting from negative shocks such as floods or the death of an earning family member. A final challenge is that the household economic surveys in which the PPI is anchored are not regularly updated, this makes poverty comparison using PPI less accurate unless the scorecards are updated regularly to capture household data from the latest economic surveys.

2.3 Microfinance and poverty

Though the impact of microfinance on poverty is extensively researched in the literature, there is little compelling evidence about the concrete relationship between microfinance and poverty. Findings of the previous research seem divided between the poverty reducing effects of microfinance (Pitt & Khandker, 1998; Khandekar, 2005; Coleman, 2006; Woutersen & Khandker, 2014), nil or insignificant benefits (Augsburg et al., 2012; Roodman & Morduch, 2009; Banerjee et al., 2015), and negative impacts on the poverty of borrowers (Bateman & Chang 2009; Karlan & Zinman, 2009). Due to absence of suitable data, at present there is no empirical evidence for the long-term benefits of participating in microfinance programmes (Asadullah & Ara, 2016). Furthermore, few studies have compared the effects of microfinance on the poverty of rural and urban borrowers. This may be because of many reasons. First, since the rural poor make up a large proportion of microfinance beneficiaries, data on urban borrowers might be too limited to make such objective poverty comparisons. Second, the researchers are more interested in evaluating the impact of microfinance on the poor, whilst assuming that, on average, rural borrowers are poorer than urban borrowers. Third, because gender targeting has been given more emphasis in microfinance research than geographical targeting. Two quasi-experimental studies (Imai & Arun, 2008; Koloma, 2013) have compared poverty reducing effects of microfinance for rural and urban borrowers. These studies show the significant poverty reducing effects of microfinance for rural borrowers and insignificant effects for urban borrowers. Narayan et al (1999) suggest that rural poverty may be less severe than in urban areas due to rural people's self-provisioning abilities, whilst others (see European commission, 2008) suggest that rural poverty is more severe due to a lack of basic services like health care, schools, roads etc. These contradictory findings of microfinance impact studies suggest that the debate on the effects of microfinance on poverty is far from over and needs more empirical research. Furthermore, there is a dearth of research using panel data for assessing the effect of microfinance on the poverty of borrowers. The novelty of this study lies in using readily available panel data for analysing poverty changes of rural and urban borrowers over time. The availability of a substantial amount of existing client–level data with MFIs provides a good opportunity for researchers to utilise such data sets in answering questions regarding the effects of microfinance.

3. DATA

We are using the readily available borrower-level panel data collected by our three partner MFIs: SVCL in India and ASKI & RSPI in the Philippines. For all three MFIs, we have more than three years of client-level data comprising of socio-economic indicators (see Table 6 in the Appendix). In particular, the data contains information on the poverty (PPI score) for each borrower, loan (loan amount, interest rates, tenure, loan cycle etc.), income of households, and individual characteristics (gender, marital status, religion, occupation, education, number of dependents and location). The data on socio-economic indicators is collected by all three MFIs as a part of the loan application and loan renewal process.

The overall data from three MFIs has 1,225,670 observations. Observations with incorrect and incomplete information were dropped from the datasets; for example, clients not matching the age criteria set by the MFIs are dropped from the analysis. In RSPI data, we find repeated entries of some loans, a few borrowers had income of more than a million Philippines Peso, some households had more than 20 household earners, etc. We also dropped clients migrating from rural to urban areas or vice versa, as including such clients would not allow for a fair comparison of urban and rural poverty over time. The final unbalanced panel data from the three MFIs contained information on 501,197 loans of 187,988 borrowers. However, due to a high attrition rate[1] of borrowers (65%-95%) across MFIs, the number of long-term borrowers staying for the full duration of the examined periods are 17,225 totalling 73,263 loans for the three MFIs. We used this balanced panel data of long-term borrowers to create matched data of borrowers with similar attributes. The final matched samples utilised for FE regression has 4,805 borrowers in total. We used both matched panel data and unbalanced data for analysing rural-urban poverty changes over time.

3.1 ASKI

Alalay Sa Kaunlaran, Incorporated (ASKI) is a Philippines based MFI providing financial services to low-income households across 12 provinces in the Philippines. The unbalanced panel data of ASKI has 35,389 rural borrowers and 6,125 urban borrowers for the period 2012-2014. Since, on average, a borrower stays for a period of 2.3 years with ASKI, the final balanced panel data has 5,655 rural borrowers and 776 urban borrowers. Due to a client attrition rate of 95%[2] during the period 2011-14 and unavailability of marital status and occupation data for 2011, a part of our analysis is based on clients staying with ASKI from 2012 until 2014. Compared to an average ASKI borrower who stays for 2.3 years, long term borrowers have a higher average PPI score by 2.1 points and are older. Compared to rural borrowers, urban borrowers have a higher PPI score by 2.6 points in 2012 and 2.4 points in 2014. Both rural and urban borrowers are middle-aged, mostly females, married and involved in trading activities. When comparing 2012 with 2014, we observed a reduced participation

[1] Attrition rate is the ratio of 'number of base year borrowers remaining at the end of the period' to 'the number of borrowers at the base year'. For example, if in 2011 a MFI has 100 borrowers, and if 90 borrowers leave MFI by 2015, attrition rate during 2011-2015 is 90%.

[2] A few borrowers (~2%) switched branches during 2011-14. Such ASKI clients received a new client ID when they borrowed loan from another branches. Accounting such borrowers in the calculation of attrition rate may lead to an improved retention rate. It is also worth specifying that clients switching branches are dropped from final data used for analysis, as location (rural/urban) of a borrower might change with branch.

of borrowers in agriculture activities and migration towards services and job sectors. *Table 1* below shows the summary statistics of the balanced and unbalanced panel data for ASKI.

Table 1: Summary statistics for ASKI borrowers, 2012-2014.

Variable	**Unbalanced Panel**	**Balanced Panel**	**Balanced Panel 2012**		**Balanced Panel 2014**	
	All borrowers	**All borrowers**	**Urban**	**Rural**	**Urban**	**Rural**
No. of borrowers	41,514	6,431	776	5655	776	5,655
PPI Score	58.8	60.9	62.72	60.14	64.38	61.96
	(16.6)	(15.9)	(14.6)	(16.5)	(13.96)	(15.7)
Age	40.9	44.3	43.3	43.3	45.5	45.50
	(14.1)	(9.83)	(10.1)	(9.7)	(10.1)	(9.8)
% Female	74.66	77.7	77.58	77.72	77.58	77.72
% Male	25.34	22.3	22.42	22.28	22.42	22.28
Marital Status						
% Married	81.01	85.61	83.89	85.64	84.54	85.87
% Separated	1.54	1.47	1.80	1.36	1.68	1.52
% Single	14.23	8.15	9.92	8.45	9.15	7.43
% Widowed	3.22	4.76	4.38	4.55	4.64	5.18
Occupation variables						
% Agriculture	20.71	21.31	19.20	23.4	12.89	20.58
% Employee	1.35	1.17	0	0.51	2.58	1.50
% Manufacturing	2.85	3.30	3.87	3.59	2.32	3.15
% Others	8.67	7.84	7.86	6.84	9.54	9.37
% Services	9.48	10.04	13.92	9.67	16.49	9.69
% Trading	56.94	56.35	55.15	55.99	56.19	55.70

Note: Standard deviation in parenthesis for variables PPI score and Age

3.2 RSPI

Rangtay Sa Pagrang-ay Inc. (RSPI) provides financial services to the poor in the North and Central Luzon parts of the Philippines. The unbalanced panel data has 47,877 rural borrowers and 8,597 urban borrowers for the period 2011-2015. During this period, on average, a client stayed for 2.63 years with RSPI. Due to a client attrition rate of 65% during the period 2011-15, a part of our analysis is based on long-term clients staying with RSPI from 2011 until 2015. The final balanced panel data used for analysis has 5,842 rural borrowers and 308 urban borrowers each year. Compared to an average RSPI borrower who stays for about 2.63 years, long term borrowers have a marginally higher average PPI score by 0.8 points, are older and on average have the same number of dependents. The average income of long-term borrowers is PHP 11,500 which is marginally lower than the mean income (PHP 11,700) of all borrowers in unbalanced data. Compared to rural borrowers, urban borrowers have a higher PPI score by 11.3 points in 2011 and 9.4 points in 2015. Urban borrowers are also more educated, have more income and fewer dependents than rural borrowers (*Table 2*). In comparison to urban borrowers, the average income of rural borrowers in 2011 is roughly lower by PHP 6,000. This difference in urban-rural income decreased to PHP 5,000 in 2015. Both rural and urban borrowers are middle-aged, mostly married females, and most employed in the service sector.

Table 2: Summary statistics for RSPI borrowers, 2011-2015.

Variable	Unbalanced Panel Data All borrowers	Balanced Panel Data All borrowers	Balanced Panel 2011 Urban	Balanced Panel 2011 Rural	Balanced Panel 2015 Urban	Balanced Panel 2015 Rural
No. of borrowers	56,474	5,842	308	5,534	308	5,534
PPI Score	52.4	53.2	58.37	47.05	65.21	55.82
	(19)	(18.9)	(18.4)	(20.5)	(15.6)	(17.7)
Age	42.6	46.7	43.61	44.90	47.47	48.83
	(11.3)	(10.5)	(10)	(10.5)	(9.9)	(10.5)
	1.7	1.7	1.6	1.72	1.63	1.73
No. of dependents	(1.6)	(1.7)	(1.4)	(1.7)	(1.4)	(1.7)
Income (in 1,000 Peso)	11.7	11.5	16.1	10.1	16.9	11.9
	(7.7)	(8.8)	(8.4)	(5.6)	(6.7)	(6)
% Female	88.57	90.55	97.08	90.46	96.75	9.96
% Male	11.43	9.45	2.92	9.54	3.25	90.04
Marital Status						
% Married	78.14	79.89	82.47	81.01	75.65	78.8
% Separated	1.9	1.85	2.92	1.93	2.27	1.52
% Single	11.95	7.73	7.14	7.82	11.04	7.61
% Widowed	8	10.52	7.47	9.23	11.04	12.07
Occupation variables						
% Agriculture	12.6	11.11	3.25	10.43	3.57	12.23
% Fishery	1.68	2.78	0	3	0	2.98
% Food Processing	2.70	2.91	3.57	3.05	1.3	2.96
% Livestock	8.42	9.03	5.84	9.22	4.87	9.36
% Manufacturing	3.18	4.27	7.14	3.92	7.79	4.3
% Services	4.69	4.43	48.7	38.63	51.3	35.94
% Trading	36.96	37.93	0.65	3	0.65	3
% Transport	3.45	2.73	22.4	24.49	20.45	24.94
% Vending	26.33	24.81	3.25	10.43	3.57	12.23
Education variables						
% College graduate	11.13	11.19	13.64	11	16.88	10.99
% College level	14.73	13.04	20.45	12.34	22.4	12.54
% Elementary graduate	12.98	15.07	4.87	14.73	6.49	15.76
% Elementary level	4.77	6.31	12.99	7.73	5.19	5.58
% High school graduate	46.05	43.96	39.29	43.78	32.47	45.34
% High school level	10.34	10.43	8.77	10.41	16.56	9.79

Note: Standard deviation in parenthesis for variables PPI score, Age, No. of dependents, and Income

3.3 SVCL

SV Creditline Private Limited (SVCL) provides microcredit for income-generating activities to poor people in seven northern Indian states with a focus on Uttar Pradesh, Madhya Pradesh and Rajasthan. The unbalanced panel data has 42,220 rural borrowers and 47,780 urban borrowers for the period 2010-2014. During this period, on average, a client stayed for two years with SVCL. Due to an attrition rate of 80% during the period 2010-14, a part of our analysis is based on long-term clients staying with SVCL from 2010 until 2014. The final balanced panel data used for analysis has 2,161 rural borrowers and 2,791 urban borrowers each year. Compared to an average SVCL borrower who stays for about two years, long term borrowers have a lower average PPI score by 1.5 points. The average income of long-term borrowers is INR 59,400, which is marginally higher than the mean income (INR 57,600) of all borrowers in unbalanced data. By comparison with urban borrowers, the average income of rural borrowers in 2010 was lower by INR 4,500. This difference in urban-rural income increased to INR 11,100 in 2014. Compared with rural borrowers, urban borrowers had a higher PPI score by 9.4 points in 2010 and 4.2 points in 2014. Most rural and urban borrowers are married, females and working as labour on daily wage basis (e.g. employed as labour in crop harvesting).

Table 3: Summary statistics for SVCL borrowers, 2010-2014.

Variable	Unbalanced Panel Data \All borrowers	Balanced Panel Data All borrowers	Balanced Panel 2010		Balanced Panel 2014	
			Urban	Rural	Urban	Rural
No. of borrowers	90,000	4,952	2,791	2,161	2,791	2,161
PPI Score	46.1	44.7	46.3	36.9	46.7	42.5
	(16.1)	(15.9)	(16.7)	(15.7)	(15.3)	(13.7)
Income (in 1000 INR)	57.6	59.4	72.2	67.7	69.5	58.4
	(32.6)	(33.1)	(52.1)	(44.6)	(17)	(4.2)
% Female	100	100	100	100	100	100
Marital Status						
% Married	96.3	96.2	95.49	97.13	95.49	97.13
% Separated	0.17	0.12	0.21	0	0.21	0
% Single	0.27	0.42	0.43	0.42	0.43	0.42
% Widowed	3.28	3.25	3.87	2.45	3.87	2.45
Occupation variables						
% Agriculture	2.37	2.71	1.86	3.79	1.86	3.79
% Animal Husbandry	4.26	4.62	3.3	6.34	3.3	6.34
% Handicraft	7.17	5.47	7.24	3.19	7.24	3.19
% Labour	44.14	43.32	36.4	52.24	36.4	52.24
% Others	26.62	23.53	25.98	20.36	25.98	20.36
% Rural Artisans	1.97	2.34	1.33	3.66	1.33	3.66
% Service	1.54	1.51	1.86	1.06	1.86	1.06
% Trade	11.94	16.5	22.04	9.35	22.04	9.35

Note: Standard deviation in parenthesis for variables PPI score and Income

4. Methodology

The present research is not intended in any way to be an impact study of microcredit on the poverty of borrowers; such research would require data on non-borrowers for comparison. Rather, it seeks to compare poverty levels of rural and urban borrowers and poverty changes over time. To address our first research question regarding the difference in poverty levels between rural and urban borrowers, we employed Propensity Score Matching (PSM). PSM allows determining the differences in poverty levels between rural and urban borrowers whilst controlling for observed individual characteristics. To test the differences in changes in poverty levels of rural and urban borrowers over time, our second research question, we applied the two way Fixed Effects (FE) regression.

Despite the methods applied, there are still methodological challenges associated with measuring the true effects of microloans. Observational data on microcredit borrowers faces the risk of sample selection bias due to several reasons: (1) self-selection, credit borrowers with certain characteristics (observable or unobservable) decide whether to apply for a microloan or not (2) endogenous placement, microfinance institutions screen or select borrowers with specific characteristics (3) attrition, borrowers with specific characteristics drop out of the dataset systematically (Imai & Arun, 2008; Verbreek, 2004). Sample selection bias produces biased coefficients, implying that the estimated effect is different from the true effect on the population, and that the results cannot be extrapolated to the general population. The sources of sample selection bias can be tested and in some cases corrected for. For the present study, we tested for attrition bias as explained in a later section.

4.1 Propensity Score Matching (PSM)

PSM provides a framework to ensure that two comparison groups are similar (Kidoido & Child, 2014). It is often used in the context of impact evaluation using observational data when experimental designs are costly or not feasible. This approach is frequently employed as an alternative to the random assignment of the treatment, because it constructs a comparable non-treatment group after the intervention has taken place. That is, it creates a comparable sample of non-treated individuals based on the most similar characteristics to the treatment group before the intervention (Leeuw & Vaessen, 2009). The present study did not involve any treatment intervention as such. However, we made use of this technique to control for the observed differences in characteristics of rural and urban borrowers when making poverty comparisons.

Rural and urban borrowers might be fundamentally different in several individual characteristics, including but not limited to, occupation, income, education, marital status, number of dependents, entrepreneurship skills, etc. By simply comparing their poverty levels, we cannot conclude whether the differences in their poverty levels are due to the effect of microfinance or due to intrinsic individual attributes. Therefore, comparing the average poverty of rural and urban borrowers without controlling for individual attributes may produce biased results. We considered urban borrowers as our 'treatment group' and rural borrowers as the 'control group'. Location (rural/urban) of borrowers was our treatment variable and PPI score was the outcome variable. Individual characteristics that simultaneously affect both the choice of location (treatment) and poverty (outcome variable) are used in the PSM model. Our choice of covariates was limited by the availability of relevant indicators in the data. Specifically, covariates used include age, gender, education, occupation, marital status, income and number of dependents. Since each of the mentioned characteristics were not available for all MFIs, the PSM models are different for the three MFIs (see Appendix 1). However, the outcome variable (PPI score) and treatment (location) is same in PSM models for all three MFIs.

The matching was done based on a propensity score, which was generated for all individuals using a probit model. Satisfaction of 'balancing property' was checked by examining whether the urban and rural borrowers have similar propensity score distribution for all variables. Observations falling in the common support region were used in the matching, and other observations were excluded from the analysis. Depending on the distribution of propensity scores in different datasets, maxima/minima (for ASKI and RSPI) or trimming technique (for SVCL) were used to identify the region of common support between rural and urban borrowers.

There are several different algorithms for matching depending on how the neighbourhood for each individual is defined, how the common support problem is handled, and how the weights are assigned to these neighbours (Caliendo & Kopeinig, 2005). We analysed the poverty levels of rural and urban borrowers using Kernel matching and employed the Nearest Neighbour (NN) matching without replacement only for comparison purposes. Kernel matching is a non-parametric algorithm that uses a weighted average of all units in common support region in the control group to construct the counterfactual (Heckman et al., 1998; Caliendo & Kopeinig, 2005). The kernel weights are determined depending on how far a treated unit is from each observation in the control group (Becker & Ichino, 2002). The Kernel matching method results in a smaller variance of the estimator since almost all information is used to create a match. We used the Epanechnikov kernel function and a bandwidth parameter of 0.06 for kernel matching. The standard errors were estimated by bootstrapping with 1,000 replications.

The PSM estimator of the difference in urban and rural poverty can be written as follows:

$$\frac{1}{N}(\sum_{i\in U} Y_i^U - \sum_{j\in R} w_{ij}\, Y_j^R \qquad (1)$$

where, Y is the outcome variable (PPI Score), *N* is the number of urban borrowers, U stands for urban borrowers, R stands for rural borrowers, and is the weight used to aggregate outcomes for the matched observations *j* in the rural group. The weight depends on the matching method used as explained above.

Since PSM method does not control for unobserved attributes, the PSM estimates could still be biased. We tested the robustness of our results against unobserved factors using sensitivity analysis, which was performed using Rosenbaum bounds. Rosenbaum (2002) proposed a bounding approach, which introduces a sensitivity parameter (Γ́) measuring robustness of estimates to the presence of unobserved factors. A sensitivity analysis tries out several values of Γ́ to see how the estimation results change. For example, if the confidence interval of estimate includes zero for Γ́>2, then the results are highly insensitive to bias. However, if this happens for Γ́=1.1, then the outcome estimate is extremely sensitive to unobserved factors. This would imply that the observed differences in poverty of rural and urban borrowers are not significantly different from zero and may be due to factors that are not observed in the model.

4.2 Two way Fixed Effects (FE) Regression

To test the differences in changes of poverty levels between rural and urban borrowers over time a panel method is required. The Difference-in-Differences (DiD) method is the most common technique because it allows estimating the changes from one time period to the next for each group. However, this estimation relies on the assumption that the two groups have a common trend. Under this assumption, rural and urban borrowers would follow the same trend towards reducing or increasing poverty over time. This assumption is difficult to hold in practice, since urban and rural borrowers could have different trends before the baseline. An alternative approach to the Difference-in-Differences method is the two way FE regression. The FE regression provides the same coefficient as the DiD method for two time periods without imposing that assumption.

The equation to estimate changes in rural-urban poverty over time is as follows:

$$Y_{it} = \sum_{t=2}^{5} \gamma_t\, T_{it} + \sum_{t=2}^{5} \beta_t\, Urban_i * T_{it} + \theta X_{it} + \alpha_i + \epsilon_{it} \qquad (2)$$

where, Y_{it} is the outcome variable i.e. the PPI score of the i^{th} borrower at time t. T_{it} represents binary variables for the year (t=2011, 2012, 2013, 2014, 2015 depending on which MFI's data is used). Therefore, γ_t captures the time effects common to all borrowers of the MFI, such as positive or negative trends in poverty levels or economic growth. $\beta_t Urban_i * T_{it}$ is an interaction term between urban area and year dummies. β_t captures the difference in changes in urban poverty to the changes in rural poverty relative to base year. In simple words, β_t allows to test our second hypothesis since it compares the changes in poverty between rural and urban borrowers over time. A negative and significant β_t coefficient implies a lower rate of change in poverty for urban borrowers compared with rural counterparts. X_{it} represents a vector of additional explanatory variables which vary with each MFI. A description of these covariates is presented in *Table 6, Appendix 1*. α_i represents the time constant individual effect, which controls for unobserved individual characteristics of the borrowers, such as entrepreneurial skills, negotiation or organizational abilities. Notice that all factors affecting the outcome variable that do not change over time, such as gender, are part of α_i and are removed by the model. Finally, ϵ_{it} is the idiosyncratic error.

Since serial autocorrelation biases standard errors in linear panel data models (Drukker, 2003), we implemented a diagnostic test proposed by Wooldridge (2010). Test results (see

Table 7, Appendix 1) suggested the presence of autocorrelation in all samples except for the matched balanced data of ASKI. Furthermore, the presence of heteroskedasticity was also tested using Modified Wald test for group-wise heteroskedasticity, the results (see

Table 7, Appendix 1) indicate the presence of heteroskedasticity in all samples. To allow for heteroskedasticity and serial correlation at individual level, we used cluster–robust standard errors.

A further issue in the econometric analysis was the risk of sample selection bias due to attrition of clients. If attrition is associated with individual characteristics of the clients, then the fixed effects estimator allows selection to depend upon α_i and it is removed by the model. Nevertheless, if attrition is systematic, e.g. poorer borrowers are more likely to drop out of the panel or excluded from future loans by the MFI, this will bias the fixed effects estimation. We tested for selection bias, following Verbeek (2004) who suggests adding a selection indicator for dropouts. For this, we included the variable **last** in the FE model and estimate equation (2) using the unbalanced panel. This variable indicates whether a borrower is observed or not in the next time period, it is a dummy variable which switches from zero to one at the time of exit. If the variable is not statistically significant, there is no indication of sample selection bias.

5. Results

In this section we only present kernel matching results for PSM and FE estimates for the interaction terms of location and time. Results of the probit model used for kernel matching are presented in *Table 8* and of detailed FE models are presented in *Table 11-Table 13* in the Appendix. The matching procedure was done over the common support region for all three MFIs to ensure that for each urban borrower we have a matched rural borrower. Appendix 2 shows that propensity scores of urban and rural borrowers overlap well in the region of common support. Differences between the mean values of each individual characteristic across urban and rural borrowers were checked before and after the matching process. This was done to ensure the satisfaction of balancing property. The results of the balancing test suggest that after matching sufficient bias reduction was achieved for most variables. Therefore, the data satisfies both assumptions of PSM. The FE regression method was used to analyse the effects of location (rural/urban) on poverty of borrowers. FE estimates of poverty changes were calculated for matched balanced panel data and unbalanced panel data. Additionally, the results of unmatched balanced panel data are presented in *Table 11-Table 13* in the Appendix.

5.1 Comparing the poverty of rural and urban borrowers using PSM

Results of the probit model estimating the probability of a client being a urban borrower are mentioned in *Table 8, Appendix 1.* The probit regression models are estimated for all three MFIs data as a precursor to implement the PSM method. The variables that are statistically significant in both years for any MFI and determines the likelihood of being an urban borrower are age, female, occupation (handicraft, labour, livestock, manufacturing, other occupations, services, trading, vending), number of dependents, education, and income (see *Table 8, Appendix 1*). The explanatory power (pseudo R^2) of probit models is fairly reasonable for RSPI (12.6%) and SVCL (17.3%), however owing to the fewer number of covariates the pseudo R^2 is low for ASKI (1.2%).

Table 4 presents a comparison of the average PPI for the matched rural and urban borrowers using the kernel matching method. The higher the PPI score (0-100), the lower the likelihood of a borrower being below a certain poverty line. The results show statistically significant differences in the poverty of borrowers for all three Asian MFIs. The quantum of poverty gap between rural and urban borrowers varies by MFI. For instance, the poverty gap for ASKI borrowers is lowest among the three MFIs. The top row of *Table 4* indicates that ASKI borrowers living in urban areas have on average a 2.4 points higher PPI score than those in rural areas. The poverty gap for ASKI borrowers remains statistically significant in 2014, but with a modest decrease (0.29 points). The largest differences in poverty scores are found among RSPI borrowers, the PPI score is eight points higher for urban borrowers than for rural clients in 2011. Despite the poverty reducing from 8.3 to 5.3 points between 2011 and 2015, the differences remain statistically significant. Furthermore, SVCL borrowers living in urban areas in 2010 had on average a 7.7 points higher PPI score than clients in rural regions. Over a period of four years the poverty gap shrunk from 7.7 in 2010 to 1.12 in 2014, which is the highest reduction among the three MFIs. Results using NN matching technique are similar to kernel matching results, we present them for comparison in

Table 9, Appendix 1.

Table 4: Propensity Score Kernel Matching results: Comparing poverty of urban and rural borrowers

Kernel Matching	Urban Borrowers	Rural Borrowers	Poverty difference
ASKI (2012)	62.72	60.30	**2.42***** (0.53)
ASKI (2014)	64.38	62.25	**2.13***** (0.53)
RSPI (2011)	58.38	50.02	**8.35***** (1.14)
RSPI (2015)	65.21	59.86	**5.34***** (0.85)
SVCL (2010)	46.16	38.46	**7.69***** (0.53)
SVCL (2014)	44.21	43.09	**1.12**** (0.50)
Note: Robust standard errors in parenthesis	***** p<0.001, ** p<0.01, * p<0.05, + p<0.10**		

The sensitivity of estimated rural-urban poverty difference to unobserved individual characteristics is calculated using Rosenbaum bounds as described in Rosenbaum (2002). Findings of the sensitivity analysis (see

Table *10, Appendix 1)* suggest that estimated rural-urban poverty difference are robust to unobserved individual characteristics for RSPI and SVCL, as confidence interval includes zero at Γ́=2.8. However, rural-urban poverty gap for ASKI is highly sensitive to the presence of unobserved factors not available in the database.

5.2 Comparing poverty changes of rural and urban borrowers over time using FE

Next, we tested whether the changes in individual PPI scores of borrowers are statistically different for rural and urban borrowers. We assessed this difference by adding interaction terms between the urban variable and time in the FE model equation (2). These coefficients capture individual changes in the PPI score of urban borrowers relative to their rural counterparts for the base year. *Table 5* shows the results of the FE model on the matched balanced panels, shown in columns 1-3, and the unbalanced panels, shown in columns 4-6. *Table 5* presents only the estimated interaction coefficients; the results of additional covariates are shown in *Table 11-Table 13* in the Appendix.

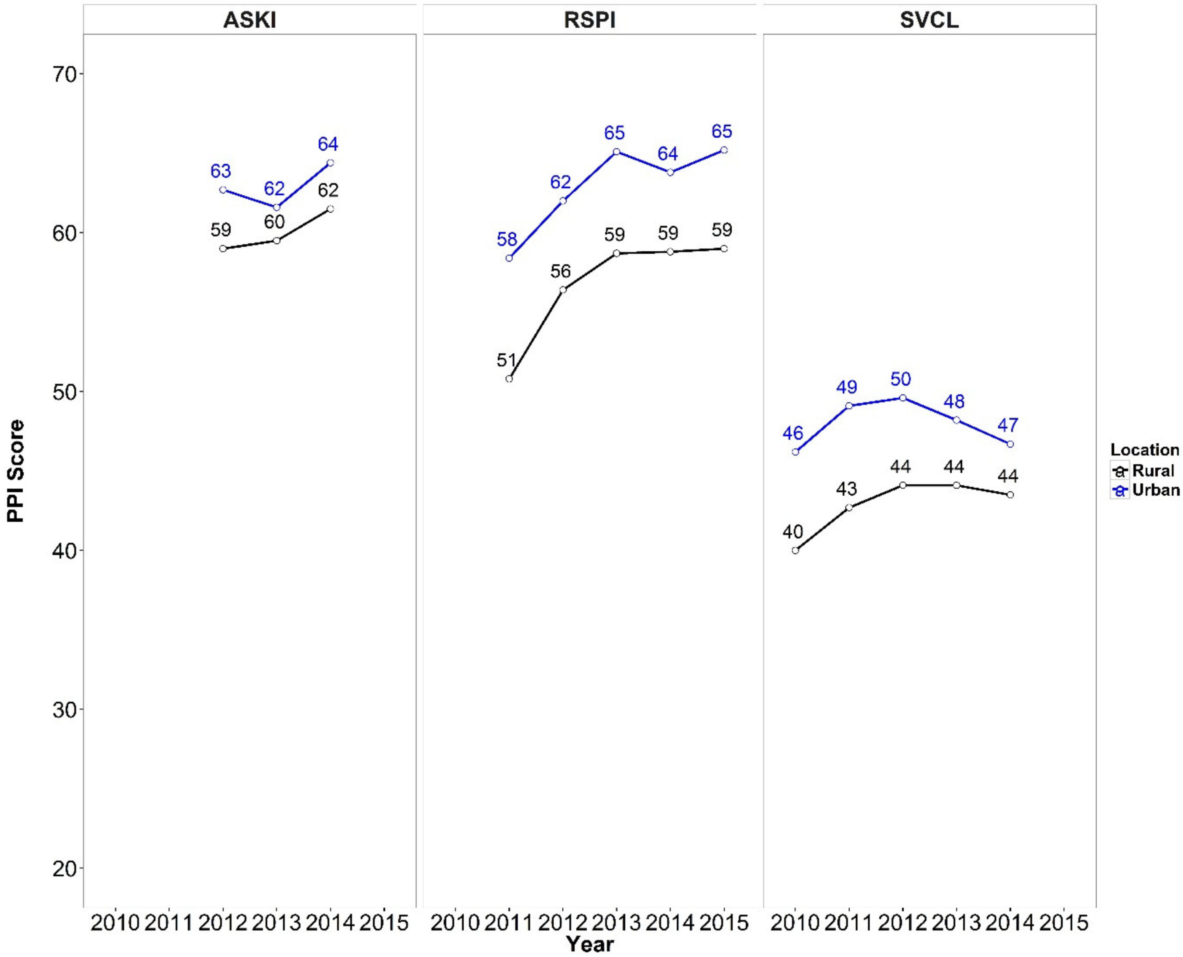
Table 5: FE estimates of the effects of location on poverty of borrowers

		Matched Balanced Panel			**Unbalanced Panel**		
		ASKI	**RSPI**	**SVCL**	**ASKI**	**RSPI**	**SVCL**
		(1)	(2)	(3)	(4)	(5)	(6)
(1)	Urban*2011			0.47			**0.57****
				(0.74)			(0.17)
(2)	Urban*2012		-2.01	-1.05		**-1.45***	**-0.54****
			(1.61)	(0.81)		(0.70)	(0.20)
(3)	Urban*2013	-1.26	-1.22	**-2.56****	**-1.39*****	-0.48	**-2.17*****
		(0.86)	(1.52)	(0.93)	(0.22)	(0.69)	(0.21)
(4)	Urban*2014	-0.87	-2.69	**-3.26****	-0.27	-1.02	**-4.73*****
		(0.97)	(1.71)	(1.03)	(0.36)	(.71)	(0.24)
(5)	Urban*2015		-1.51			-0.62	
			(1.64)			(0.71)	
(6)	Last				**-0.75*****	**-0.71*****	0.11
					(0.18)	(0.13)	(0.08)
	Base year	2012	2011	2010	2012	2011	2010
	No of obs.	3,285	2,905	15,645	89,341	159,373	252,453
	No. of clients	1,095	581	3,129	41,501	56,474	90,000
	R^2	0.02	0.07	0.02	0.01	0.03	0.01
	F	7.68	10.96	31.98	90.02	203.6	257.6
	p-value	0.00	0.00	0.00	0.00	0.00	0.00

Note: Cluster-robust standard errors in parenthesis ***** p<0.001, ** p<0.01, * p<0.05, + p<0.10**

Using the matched samples, we found no statistically significant differences in the rate of change of poverty of rural and urban borrowers in most cases. The exceptions are the interaction terms Urban*2013 and Urban*2014 for SVCL (*Table 5*, column 3). The coefficient Urban*2013 indicates that the rate of change in the PPI Score of SVCL's rural borrowers was on average two points higher than for those clients located in urban areas. To illustrate, urban borrowers from SVCL increased their PPI Score from an average of 46 points in 2010 to 48 points in 2013; over the same time period, rural borrowers increased their PPI score by four points, from 40 to 44. Thus, the difference in the rate of change of urban-rural poverty is -2 points, as indicated by the coefficient Urban*2013. Changes in the poverty of similar (matched) urban and rural borrowers over time are also depicted below in *Figure 1*.

Figure 1: PPI Scores of rural and urban borrowers, matched samples.

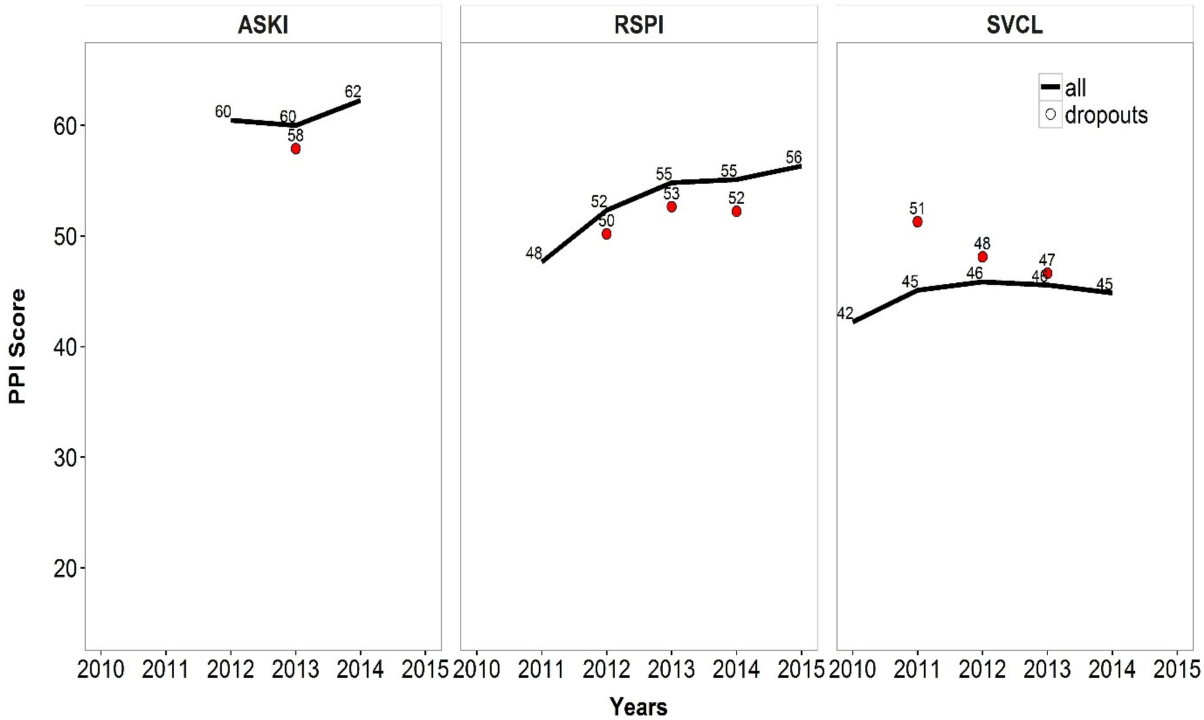


The differences between rural and urban borrowers become more evident when analysing the unbalanced panels (*Table 5*, columns 4-6). Differences in the rate of change become statistically significant for ASKI borrowers in 2013 and RSPI borrowers in 2012, whereas for SVCL the differences are significant over the entire period of the analysis. The negative coefficients indicate that urban borrowers are increasing their PPI scores but at a lower rate than their rural counterparts, implying a shrinking poverty gap relative to the base year. This finding is consistent with previous studies (Imai & Arun, 2008; Koloma, 2013), which have demonstrated that the poverty reducing effects of microfinance are higher for rural borrowers than for urban borrowers. A coefficient of the number of dependents for unbalanced RSPI data suggests that for every additional dependent in a family the PPI score of a household decreases by 0.74 points. This finding is consistent with Gang et al (2008), which suggests that poverty increases with household size.

Rural borrowers from RSPI showed larger changes in the housing conditions compared to urban borrowers. Specifically, the data shows improvements in the building material of walls and roofs from light materials (cogon, nipa or bamboo) to stronger and safer elements (iron, aluminium, etc.). Rural borrowers from SVCL, compared to urban counterparts, showed larger changes in the expenditure for purchase of durable goods for domestic use such as crockery and utensils and they became more often self-employed.

We use the variable **last** in *Table 5* (row 6) as an indicator for the presence of attrition bias, as suggested by Verbeek (2004). It identifies a borrower in the year of exit in the unbalanced panel data. Results in *Table 5* show that ASKI and RSPI borrowers who dropped out of the panel have significantly different PPI scores during the year of exit. Their PPI score is 0.7 lower compared to those who stayed with the MFI for an additional year[3] (see also *Figure 2*). The differences in the PPI score are negligible but statistically significant, which suggests that attrition is negatively correlated with the PPI score of the borrowers. The results for SVCL show no evidence of sample bias and the PPI score of SVCL borrowers upon exit is positive but insignificant. Interestingly, this positive coefficient contradicts the general belief practitioners have that client attrition could only have a negative correlation with the outcome variable. Hence, the effect of attrition bias can take place in both directions, depending on whether borrowers have increased or decreased their poverty levels at the time of exit.

Figure 2: PPI Scores of all borrowers and drop-outs in unbalanced panel data



6. CONCLUSIONS

Providing access to financial services for low income people is crucial to open opportunities for their socio-economic development. The potential gains from microfinance have been recognized by many donors, social investors and microfinance institutions, which in many cases have decided to prioritize rural regions in developing countries, presuming larger social returns on their investments. However, there is a lack of empirical evidence showing whether this geographical targeting is an effective decision for reducing poverty. To address this problem, this research analysed three pro-poor credit market interventions and identified the effects of these interventions on the poverty levels of rural and urban borrowers. As case studies, we used data from three microfinance institutions in Asia: ASKI (2012-2014), RSPI (2011-2015) in the Philippines and SVCL in India (2010-2014).

We used readily available data on the socio-economic characteristics of the borrowers collected by MFIs during each loan cycle. The PPI is the variable we employed for measuring poverty at borrower

[3] Furthermore, we analyse the PPI score of rural and urban dropouts and found no consistent differences.

level. To compare poverty levels while controlling for inherent differences between rural and urban borrowers, we used PSM. PSM allows constructing two groups of borrowers (rural and urban) with similar individual characteristics and testing their poverty levels at different points in time. Additionally, to determine the differences in changes of poverty levels between rural and urban borrowers, we employed the two way Fixed Effects (FE) method for panel data. The PSM results indicate that across three MFIs, rural borrowers are poorer than similar urban borrowers. The panel data analysis also indicated that by comparison with urban clients, rural borrowers experience higher reduction in their poverty levels over time, leading to a narrowing of the urban-rural poverty gap. Despite some reduction in the poverty gap, the differences remain persistent over the examined periods, indicating that additional efforts are necessary to reduce poverty in rural regions. Future research may run the analysis for longer periods of time to determine whether the poverty gap is persistent over the long term. Overall, these results provided empirical evidence that targeting disadvantaged rural people through these three pro-poor credit market interventions was an effective strategy to further reduce poverty in these areas.

We acknowledge the limitations of this study. The results presented here are conditional on taking a micro loan from one of these three MFIs and cannot be directly generalized to other borrowers in other contexts. Additionally, we recognize the problem of attrition bias on our results. The results showed that borrowers not taking an additional loan had a lower PPI at the time of exit. Since the data sets lacked information on the reasons for dropping-out, we could not create controls for this problem. This also suggests that further work is needed to find appropriate ways to address the attrition issue. Recognizing and addressing this problem is crucial for the microfinance sector in general: for academic economists, because understanding the process of attrition can help them to control for it and for practitioners, because it will shed light on the reasons behind client exit and determine whether the products and conditions they offer meets the need of the low income population.

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Appendix-1: Variables used and Results of PSM & Fixed Effects models

Table 6: List of variables used in poverty analysis of borrowers from 3 MFIs

Variables	**ASKI**	**RSPI**	**SVCL**
PPI Score	X	X	X
Age	X	X	
No. of Dependents		X	
Income		X	X
Gender	X	X	X
Occupation	X	X	X
Education		X	
Marital status	X	X	X

Table 7: Autocorrelation and heteroskedasticity test results

	SVCL Unbalanced	SVCL Matched Balanced	RSPI Unbalanced	RSPI Matched Balanced	ASKI Unbalanced	ASKI Matched Balanced
			Wooldridge test for autocorrelation			
F-statistic	356.24	55.78	605.28	35.79	48.59	3.70
P-value	0	0	0	0	0	0.05
			Modified Wald test for group-wise heteroskedasticity			
Chi2	$1.80 * 10^{38}$	$5.10 *10^{5}$	$7.30* 10^{37}$	$2.70* 10^{5}$	$4.10* 10^{38}$	$5.10 * 10^{8}$
P-value	0	0	0	0	0	0

Table 8: Probit model results used for propensity score matching method

	ASKI 2012	ASKI 2014	RSPI 2011	RSPI 2015	SVCL 2010	SVCL 2014
	0.0008	0.0018	-0.0089**	-0.0070*		
Age	(0.00)	(0.00)	(0.00)	(0.00)		
	-0.14	-0.03	-0.18	-0.34	-4.72	-4.81
Married	(0.16)	(0.16)	(0.19)	(0.21)	(94.37)	(104.42)
	-0.06	0.07	-0.22	-0.15	-4.66	-4.87
Single	(0.17)	(0.18)	(0.22)	(0.23)	(94.37)	(104.42)
	-0.15	-0.09	-0.15	-0.29	-4.42	-4.49
Widow	(0.19)	(0.19)	(0.22)	(0.23)	(94.37)	(104.42)
	-0.02	-0.06	0.53**	0.51***		
Female	(0.05)	(0.06)	(0.16)	(0.15)		
					0.025	0.03
Animal husbandry					(0.14)	(0.14)
					-0.21	-0.26
Artisans					(0.16)	(0.17)
					0.93***	0.78***
Handicraft					(0.14)	(0.15)
		0.54***				
Employee		(0.15)				
			0.68**	0.2901		
Food processing			(0.20)	(0.25)		
					0.21+	0.25**
Labour					(0.11)	(0.12)
			0.37*	0.30+		
Livestock			(0.17)	(0.17)		
	0.16	0.11	0.91***	0.88***		
Manufacturing	(0.12)	(0.14)	(0.18)	(0.17)		
	0.19*	0.27***			0.59***	0.45***
Others	(0.09)	(0.09)			(0.12)	(0.12)
	0.31***	0.54***	0.82***	0.93***	0.77***	0.60
Services	(0.07)	(0.08)	(0.17)	(0.16)	(0.19)	(0.21)
	0.11*	0.27***	0.63***	0.75***	0.95***	0.77
Trading	(0.06)	(0.06)	(0.14)	(0.13)	(0.12)	(0.13)
Transport			0.05	-0.01		

			(0.33)	(0.33)		
			0.56***	0.57***		
Vending			(0.14)	(0.14)		
			-0.04*	-0.05*		
Dependents			(0.02)	(0.02)		
			0.05***	0.04***	0.0005	0.0001***
Income			(0.00)	(0.00)	(0.00)	(0.00)
			-0.05	-0.46***		
High school graduate			(0.10)	(0.09)		
			0.28*	-0.23		
Elementary level			(0.13)	(0.15)		
			-0.43**	-0.65***		
Elementary graduate			(0.15)	(0.13)		
			0.16	-0.07		
College level			(0.12)	(0.10)		
			-0.02*	-0.28**		
College graduate			(0.13)	(0.11)		
	-1.17***	-1.45***	-2.62***	-2.23***	4.39	0.97
Constant	(0.19)	(0.20)	(0.33)	(0.34)	(94.37)	(104.42)
No. of observations	6430	6430	5842	5842	4952	4952
Joint significance	LR chi2(9)=21.43	LR chi2(9)=58.87	LR chi2(19)=308.15	LR chi2(19)=303.35	LR chi2(11)=340.75	LR chi2(11)=1174.4
Log likelihood	-2355.37	-2355.10	-1052.02	-1054.42	-3221.90	-2805.08
Pseudo R^2	0.05	0.01	0.13	0.13	0.05	0.17

Table 9: Comparing the poverty of urban and rural borrowers using NN Matching results

Nearest Neighbour Matching	**Urban Borrowers**	**Rural Borrowers**	**Poverty difference**
ASKI (2012)	62.72	60.17	2.55^{+} (1.49)
ASKI (2014)	64.38	60.23	4.14** (1.44)
RSPI (2011)	58.38	50.83	7.54*** (2.01)
RSPI (2015)	65.21	62.04	3.17** (1.57)
SVCL (2010)	46.16	38.33	7.83*** (1.44)
SVCL (2014)	44.21	41.65	3.05 (5.05)
Note: Robust standard errors in parenthesis		***** p<0.001, ** p<0.01, * p<0.05, + p<0.10**	

Table 10: Sensitivity analysis for urban-rural poverty difference

	95% Confidence Intervals					
	ASKI (2012)		**RSPI (2011)**		**SVCL (2010)**	
Gamma (Ѓ)	**Lower**	**Upper**	**Lower**	**Upper**	**Lower**	**Upper**
1	1.7	3.9	7.9	11.5	7.3	8.6
1.1	1.0	4.5	7.2	12.2	6.6	9.2
1.2	0.5	5.2	6.6	12.8	6.0	9.9
1.3	-0.1	5.7	5.9	13.3	5.4	10.5
1.4	-0.6	6.1	5.3	13.8	4.8	11.0
1.5	**-1.1**	**6.6**	4.8	14.3	4.3	11.5
1.6	-1.5	6.9	4.3	14.7	3.8	12.0
1.7	-1.9	7.4	3.9	15.1	3.4	12.4
1.8	-2.2	7.8	3.4	15.5	3.0	12.8
1.9	-2.6	8.0	3.0	15.8	2.6	13.2
2	-3.0	8.4	2.5	16.2	2.2	13.6
2.1	-3.3	8.7	2.1	16.5	1.9	13.9
2.2	-3.6	9.0	1.7	16.8	1.5	14.2
2.3	-4.0	9.3	1.4	17.1	1.1	14.5
2.4	-4.2	9.5	1.0	17.3	0.9	14.8
2.5	-4.5	9.8	0.7	17.6	0.6	15.1
2.6	-4.8	10.1	0.4	17.8	0.3	15.4
2.7	-5.1	10.3	0.0	18.1	0.0	15.6
2.8	**-5.3**	**10.4**	**-0.3**	**18.3**	**-0.3**	**15.9**

Table 11: ASKI Fixed Effect Results

ASKI	Unmatched Balanced Panel	Matched Balanced Panel	Unbalanced Panel
Year=2013	-0.66*	-0.31	-0.57**
	(0.28)	(0.90)	(0.20)
Year=2014	1.14*	1.47	1.80***
	(0.56)	(1.48)	(0.41)
Urban*2013	-0.79	-1.26	-1.39***
	(0.51)	(0.86)	(0.22)
Urban*2014	-0.20	-0.87	-0.27
	(0.55)	(0.97)	(0.36)
Age	0.06	-0.23	-0.59*
	(0.44)	(1.01)	(0.25)
Age Square	0.003	0.008	0.010***
	(0.004)	(0.009)	(0.003)
Last			-0.75***
			(0.18)
Intercept	52.47***	56.55*	64.91***
	(12.97)	(30.48)	(6.93)
No of observations	19293	3285	89341
R^2	0.0148	0.02	0.01
F	31.82	7.68	90.02
No of clients	6431	1095	41501
P	3.91e-32	0.000000412	$1.07 * 10^{-112}$
Note: Cluster-robust standard errors in parenthesis.		***** p<0.001, ** p<0.01, * p<0.05, + p<0.10**	

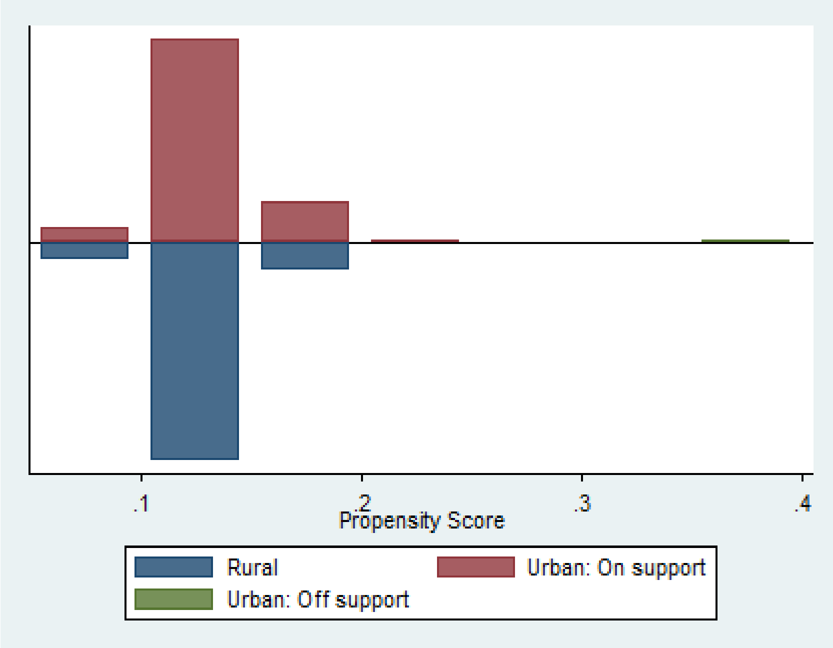
Table 12: RSPI Fixed Effect Results

RSPI	Unmatched Balanced Panel	Matched Balanced Panel	Unbalanced Panel
Year=2012	4.37***	6.66***	3.52***
	(0.36)	(1.37)	(0.20)
Year=2013	6.44***	9.92***	5.57***
	(0.54)	(1.97)	(0.29)
Year=2014	6.41***	11.04***	5.89***
	(0.78)	(2.75)	(0.40)
Year=2015	7.27***	12.26***	7.19***
	(1.00)	(3.64)	(0.56)
Urban*2012	-1.09	-2.01	-1.45*
	(1.20)	(1.61)	(0.70)
Urban*2013	-0.48	-1.22	-0.48
	(1.08)	(1.52)	(0.69)
Urban*2014	-2.17+	-2.69	-1.02
	(1.20)	(1.71)	(0.71)
Urban*2015	-1.94+	-1.51	-0.62
	(1.13)	(1.64)	(0.71)
No of dependents	-0.81***	-0.55	-0.74***
	(0.18)	(0.65)	(0.08)
Age	0.72+	-1.66	0.37+
	(0.37)	(1.18)	(0.19)
Age square	-0.004	0.007	0.001
	(0.003)	(0.009)	(0.002)
Last			-0.71***
			(0.13)
Intercept	24.35+	113.6**	30.57***
	(12.75)	(41.35)	(5.67)
No of observations	29210	2905	159373
R^2	0.08	0.07	0.03
F	109.7	10.96	203.6
No of clients	5842	581	56474
P	9.13e-210	3.29e-17	0
Note: Cluster-robust standard errors in parenthesis.		***** p<0.001, ** p<0.01, * p<0.05, + p<0.10**	

Table 13: SVCL Fixed Effect Results

SVCL	**Unmatched Balanced Panel**	**Matched Balanced Panel**	**Unbalanced Panel**
Year=2011	2.80***	2.43***	2.34***
	(0.28)	(0.69)	(0.14)
Year=2012	3.95***	4.48***	3.70***
	(0.32)	(0.86)	(0.15)
Year=2013	5.13***	4.52***	4.78***
	(0.35)	(0.87)	(0.17)
Year=2014	5.57***	3.72**	5.89***
	(0.40)	(0.96)	(0.22)
Urban*2011	0.14	0.47	0.57**
	(0.38)	(0.74)	(0.17)
Urban*2012	-0.58	-1.05	-0.54***
	(0.43)	(0.81)	(0.20)
Urban*2013	-3.21***	-2.56*	-2.17***
	(0.48)	(0.93)	(0.21)
Urban*2014	-5.23***	-3.26**	-4.73***
	(0.54)	(1.03)	(0.24)
Last			0.11
			(0.08)
Intercept	42.22***	45.39***	43.03***
	(0.15)	(0.185)	(0.08)
No of observations	24760	15645	252453
R^2	0.02	0.02	0.01
F	61.95	31.98	257.6
No of clients	4952	3129	90000
P	9.19e-86	3.81e-43	0
Note: Cluster-robust standard errors in parenthesis.		***** p<0.001, ** p<0.01, * p<0.05, + p<0.10**	

Appendix-2: Distribution of Propensity Score in the Common Support Region for rural and urban borrowers



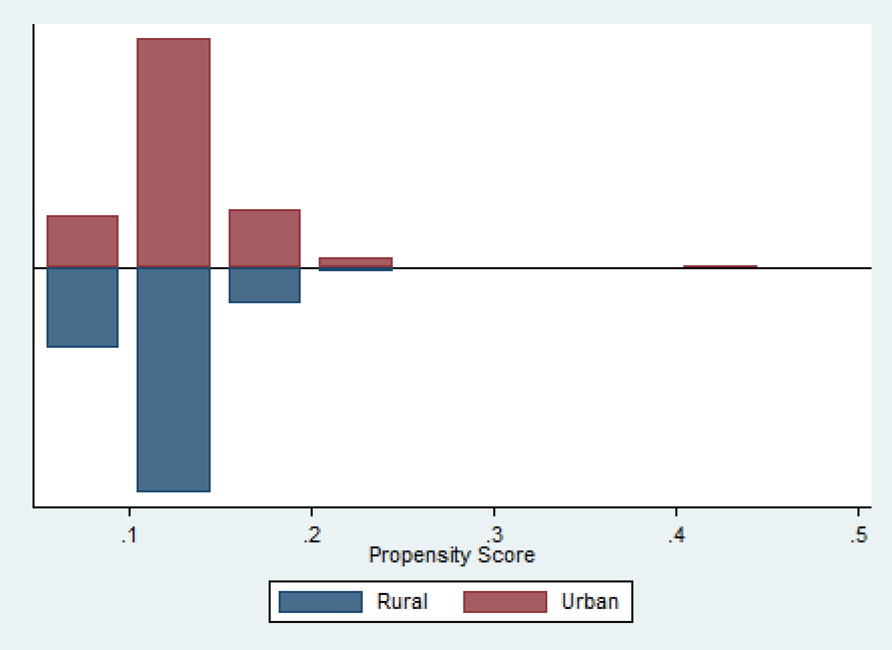
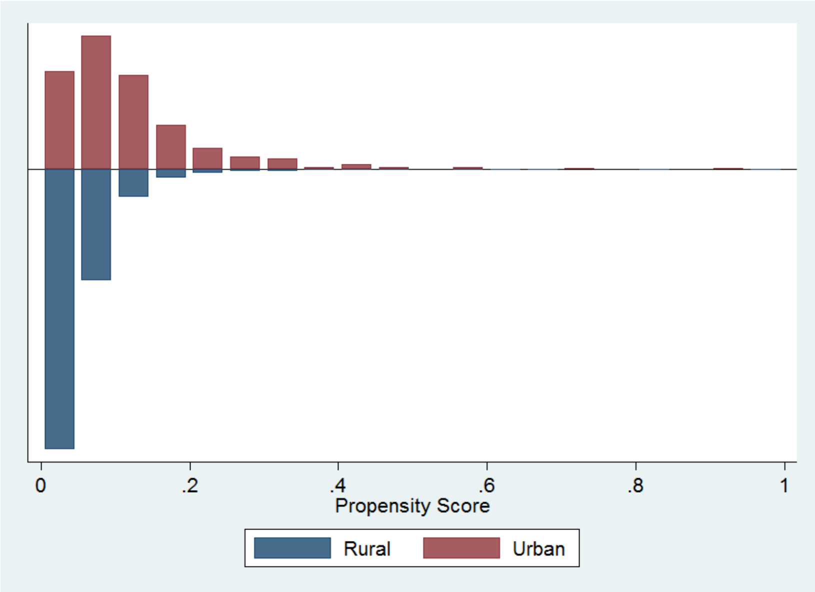


Figure 3: ASKI data for 2012

Figure 4: ASKI data for 2014



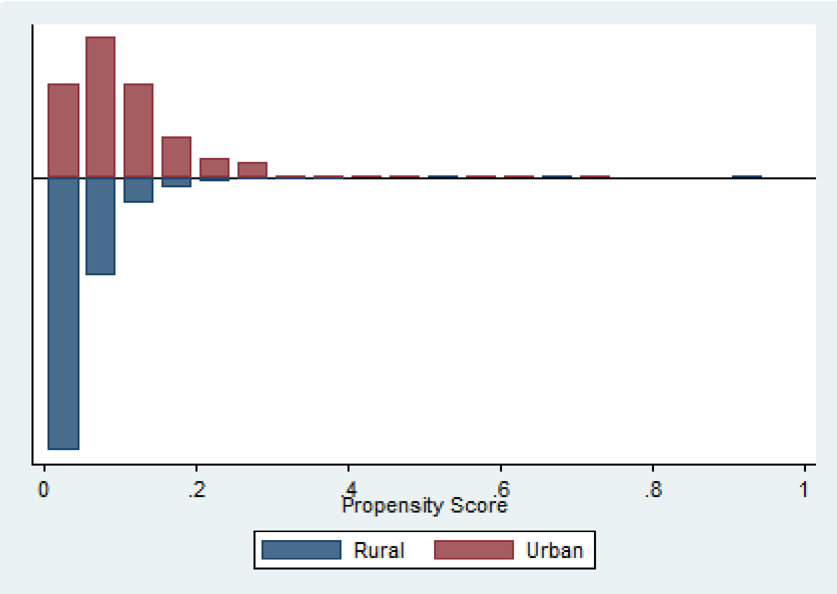


Figure 5: RSPI data for 2011

Figure 6: RSPI data for 2015

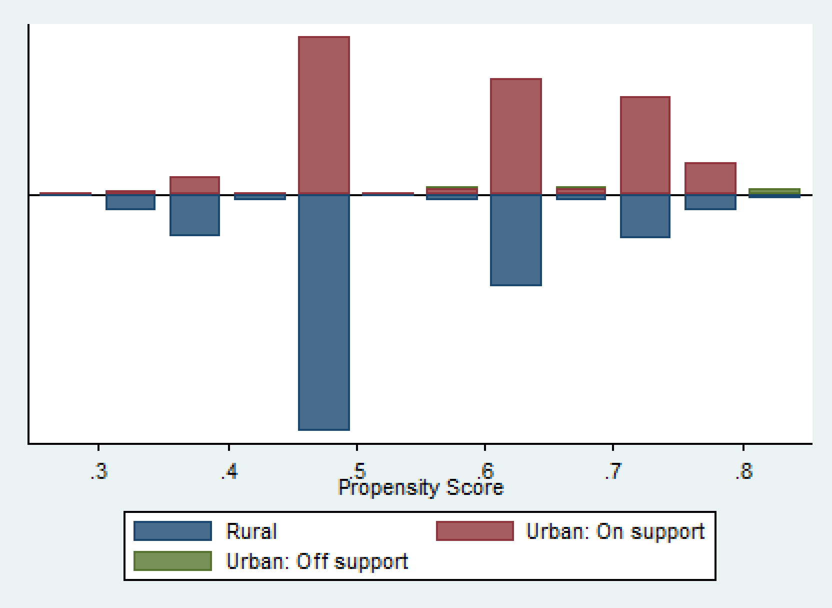


Figure 7: SVCL data for 2010

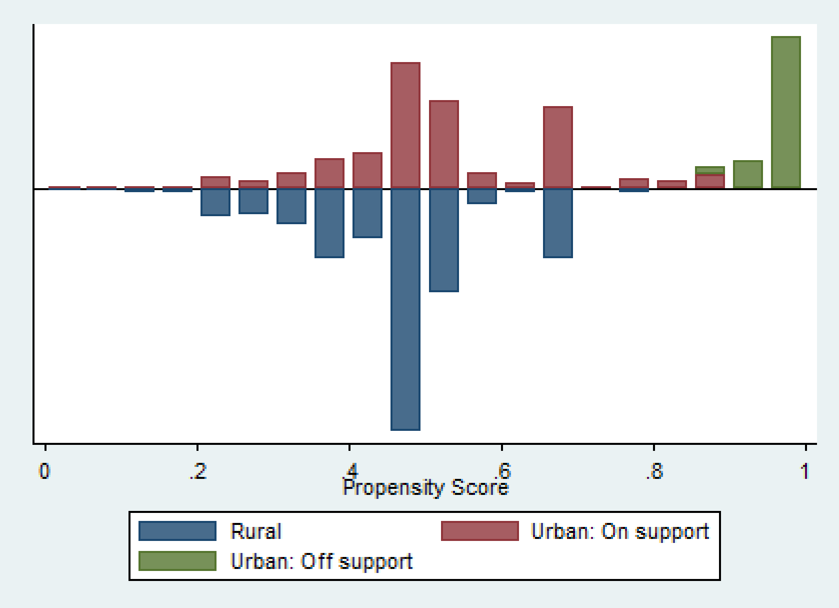


Figure 8: SVCL data for 2014