Effects of Microcredit on the Poverty of Borrowers using the Progress out of Poverty Index: Evidence from Asian MFIs

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Abstract

This discussion paper uses unbalanced panel data from more than one million poverty records spanning more than four years to analyse the influence of microcredit on poverty of borrowers in India and the Philippines. The uniqueness of this paper is its use of the Progress out of Poverty Index (PPI) for poverty measurement. We apply a fixed-effects regression model to study the effect of microfinance on the poverty of microcredit borrowers over time at individual level, and pooled OLS regression to analyse factors associating with client's poverty. The econometric analysis suggests that microfinance loans have a small positive and significant effect on poverty reduction among microcredit borrowers. Other variables such as annual household income, and individual attributes such as location and occupation also explain poverty changes.

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1. Introduction

Microfinance has reached approximately 130-200 million[1,2] poor people globally, of which around 37.5 million[3,4] are based in India and the Philippines. Although these numbers look impressive, they only signal the success of microfinance in reaching the poor. The role of microfinance in reducing poverty has been, and is still, rigorously debated in the literature (Bateman 2010; Robinson 2001). Previous research seems divided between the positive effects of microfinance (Sebstad and Chen 1996; Pitt and Khandker 1998; Khandekar 2001; Khandekar 2005; Imai et al. 2010; Imai and Azam 2010), nil or insignificant benefits (Copestake et al. 2001; Hulme and Mosley 1996; Morduch 1998; Mosley and Hulme 1998, Hulme 2000; Zaman 2001), and negative impacts (Adams and Von Pischke 1992; Bateman & Chang 2009; Rogaly 1996, Rooyen et al. 2012). Although various studies have been done, there is very little overall compelling evidence demonstrating the relationship between microcredit and poverty reduction (e.g. Banjeree, Duflo et al. 2009; Crépon et al. 2011; Khandker and Samad 2013).

This discussion paper analyses the influence of microfinance loans on the poverty levels of borrowers using readily available management information system data from two leading microfinance institutions (MFIs), namely SVCL and ASKI, based in India and the Philippines respectively. The study is unique because we examine an unbalanced panel dataset of more than 600,000 borrowers with data on the Progress out of Poverty Index (PPI).[5] We apply fixed-effects regression analysis to study the influence of microfinance on the poverty of microcredit borrowers at individual level, and pooled OLS to understand factors associating with client's poverty. In doing so, we do not estimate poverty impacts because we lack a control group and clients were not randomized, yet we contribute to the growing literature on the relationship between microcredit and poverty by analysing readily available and large sample monitoring data. We further argue that the analytical methods applied in this study are cost effective and can be easily scaled up to other MFIs.

Section 2 shows a literature review on microfinance and poverty alleviation, and the PPI scorecard. Section 3 describes the data. Section 4 presents the methodology for data analysis. Section 5 demonstrates our empirical findings and Section 6 presents conclusions.

2. Literature review

Microfinance's effect on poverty reduction has been fiercely debated. Extreme normative views argued that microfinance reduces poverty because it stimulates income-generating opportunities (Robinson 2001; Von Pischke 1991), while others argued the exact opposite: it hurts the poor and much more is needed to lift borrowers above the poverty line (Dichter 2005; Bateman and Chang 2009). More evidence-based approaches using social performance and impact evaluations find mixed relationships between microcredit and poverty reduction. Early studies used quasi-experimental evaluation using panel data; for example, Khandker (2001) found that programme participants are better off in terms of per capita income, per capita expenditure, and household net worth when compared to the control group. Morduch and Haley (2002) found that microfinance had positive impacts on eradicating extreme poverty. Using panel household survey

[1] http://www.ifc.org/wps/wcm/connect/Industry_EXT_Content/IFC_External_Corporate_Site/Industries/Financial+Markets/MSME+Finance/Microfinance/

[2] Khandekar and Samad (2013)

[3] http://www.sa-dhan.net/Resources/Finale%20Report.pdf

[4] http://www.mixmarket.org/mfi/country/Philippines

[5] The PPI tool does not directly identify the poverty of a client, but reports poverty likelihoods. However, averaging poverty likelihoods for samples of individuals gives the absolute poverty rate of the group.

data from Bangladesh, Khandker and Pitt (2003) demonstrated that microcredit reduced the average village poverty level by 1% each year. They observed a higher impact on extreme poverty than on moderate poverty. Khandker (2005) confirms that microfinance programmes have a positive impact in terms of reducing poverty among participants and detect a positive spillover effect at village level. However, Khandker and Samad (2013) caution that accrued gains in income and consumption from microfinance is merely temporary and not sustainable in the long term. Coleman (2004) also found that village-bank credit programmes in Thailand did not significantly impact the income, savings and expenses of borrowers. Irmai and Arun (2008) used propensity score matching and found that access to microfinance in India reduced poverty as measured by a multi-dimensional poverty index. Effects differed across rural and urban areas and for the poor and moderately poor borrowers (Imai and Arun 2008). Islam (2011) and Khandker and Samad (2013) both found that clients derive more income and consumption gains when they participate in microcredit programmes for a longer duration.

Later studies using randomized control trials found mixed effects of microfinance on poverty reduction, with several finding positive effects of microfinance on poverty indicators (Karlan and Zinman 2009; McKenzie and Woodruff 2008; de Mel et al. 2008), and others finding no clear evidence that microfinance reduces poverty (Augsburg et al. 2011; Attanasio et al. 2012; Banerjee et al. 2010; Karlan and Zinman 2011; Crepon et al. 2001). For example, Crepon et al. (2011) demonstrate that access to microcredit can result in income-generating activities for specific types of borrowers. Access to credit increased clients' sales and expenses, but no wider impacts were measured on poverty (Crepon et al., 2011:11-12). Banjeree, Duflo et al. (2009)'s study on an urban microcredit programme in India found overall incomes did not increase, but expenses on durables did.

A variety of authors point out that the studies carried out are difficult to compare and their findings are highly mixed because they apply to different contexts, employ various methodologies and metrics, and microfinance itself is a highly heterogeneous intervention. There is little overall compelling evidence that microfinance has a strong effect on poverty and more research is needed (Armendariz and Morduch 2008; Balkenhol 2007; Copestake et al. 2005; Karnani 2007).

Progress out of Poverty Index

There are many ways of measuring poverty in microfinance, including income lines (Honohan 2007; Chen and Revallion 2008), livelihood (Sen 1999) and wellbeing approaches (e.g. Gough and McGregor, 2007). The last decade in particular has seen a trend towards measuring income-poverty using scorecard systems such as the Progress out of Poverty Index (PPI) (Chua et al. 2013; Ford Foundation 2010; Grameen Foundation 2014). The PPI is a scorecard using only ten questions on household assets and other characteristics to measure the probability that a household lives below a certain income line such as the international poverty lines of US$ 1.25 or US$ 2.50 per day or the national poverty line (NPL) (Chua et al. 2012:3). The scorecard makes objective measurements because the survey questions and PPI scores are linked to national household surveys data (Schreiner 2008).

The PPI was developed in response to the need to have more cost-effective and practical tools that measure the percentage of people living in poverty. Conventional tools using income and expenditure-based poverty indices were generally considered costly and time-consuming to collect as well as prone to measurement error (Deaton, 1997). According to a systematic review for the Ford Foundation (2010), the PPI is generally believed to be cheaper than conventional ways of assessing incomes and expenses. 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.

The PPI scorecard has particularly gained acceptability in the microfinance industry (Social Performance Taskforce 2010). Worldwide, over 200 organizations in 45 countries apply the tool, of which the majority are MFIs (around 71%) (Grameen 2014). Data from Oikocredit shows that the PPI is the most popular poverty measurement tool; out of 134 MFIs tracking the poverty levels of their borrowers, 83 applied it (Oikocredit, 2014). Although the PPI is widely used to quantify the percentage of clients in comparison to the country benchmark (Dinh and Zeller 2010; Ford Foundation 2010:15-22), and others have applied it for external impact evaluation (e.g. lo

One challenge in capturing changes in poverty levels over time using PPI measurement is that the score is highly sensitive to some questions and insensitive to others. For example, as Polk and Jonhson (2009) point out, it is extremely difficult to progress from a score of 95 because in order to do so, one must improve on one question that did not initially grant full points. Desiere, Vellma and D'Haese (2014) criticized the PPI tool for its limited sensitivity to changes in poverty status resulting from negative shocks. Using the PPI scorecard for Rwanda they demonstrated that only two questions were responsible for explaining 80% of the observed variation over time. Carter and Barrett (2006) state that sensitivity to both upward and downward movements in assets is crucial in order to make PPI a valuable indicator to study poverty traps. Other indicators such as the increase in the number of cell phones or TVs owned may only weakly explain actual household income changes because rapid product innovation makes these products more affordable for consumers (Ford Foundation 2010). A final challenge is that the household economic surveys in which the PPI is anchored, are not regularly updated and new versions of the scorecards cannot always be easily compared to older versions (Ford Foundation 2010). Thus the main strength of the tool, using only 10 questions to estimate poverty, may also be its Achilles heel.

Aside from methodological challenges, MFIs may also lack capacity to handle longitudinal analysis and track changes in client outcomes over time (Gravesteijn 2014). A review of the PPI methodology highlighted that MFIs showed very different levels of human and financial resources to implement scorecards and often lacked management information system (MIS) and staff training systems (Ford Foundation 2010). Underlying this could be deeper issues of organizational culture and drivers, for example is data used proactively to stimulate internal operations, or merely to demonstrate impacts to outsiders (Gravesteijn 2014)?

Another challenge hindering the MFI's ability to monitor its social objectives is the cost associated with monitoring and impact evaluation (Morduch and Haley 2002). Impact assessment methodology can be expensive and there are real concerns that results do not always lead to sustained improvements in the MFI's social performance management (Copestake et al. 2005:212; Gravesteijn 2014). Taking into account the cost-effectiveness argument, several authors have opted to use regular client-outcome monitoring (Imp-Act 2004). By way of example, four case studies demonstrated that low-cost client-outcome monitoring yielded significant economic benefits including reduced exit rates, new product modifications, and improved uptake of savings and loans by clients. Advocates of controlled randomized sample studies have been highly critical of this view and argue that at all times a control group is required to assess impacts (Karlan and Goldberg 2007; Duflo et al 2007; Banerjee, Duflo et al 2009).

We acknowledge this view as a limitation in our study and do not claim to assert poverty impacts. Nonetheless, assessing the readily available monitoring data adds value because of the sheer size of the datasets that are collected as part of the MFIs' routine credit operations. This discussion paper contributes to the existing research on MFIs' social performance. In particular, we focus on the PPI data of two MFIs: SVCL in India and ASKI in the Philippines, and assess the influence of microfinance loans on clients' poverty levels. We also take into account the costing of the study itself.

3. Data

This paper uses the client level panel data obtained from the management information systems of SVCL and ASKI. We have unbalanced panel data for five years (2010-2014) for SVCL, and for four years (2011-14) for ASKI. The data contains information on microfinance loans (the loan amount, tenure and loan cycle), annual household income, and individual characteristics (gender, marital status, occupation and location). The final samples contain unbalanced panel data for about 600,000 microcredit borrowers over a period of four years. We use the PPI score as a proxy for poverty. The poverty rates and likelihoods mentioned pertain to the national poverty line (NPL) of India and the Philippines.

3.1 SVCL Data

SV Creditline Private Limited (SVCL) provides small credit for income-generating activities operating from seven northern Indian States with a focus on Uttar Pradesh, Madhya Pradesh and Rajasthan. Figure 1 and 2 show that during the period 2010-14, the total loan portfolio of SVCL increased by over six times and the number of active borrowers more than quadrupled. Strong growth came in parallel with high client attrition rates; for example a survival analysis of all 59,250 clients who joined SVCL in 2010 showed that around 23,748 (40%) remained active after January 2012, 12,388 (21%) remained active after January 2013 and 14% remained active after January 2014 (see Table 7 in the Annex) This could suggest that microcredit is not a long-term intervention for the majority of clients.

Figure 1: SVCL growth in loan portfolio

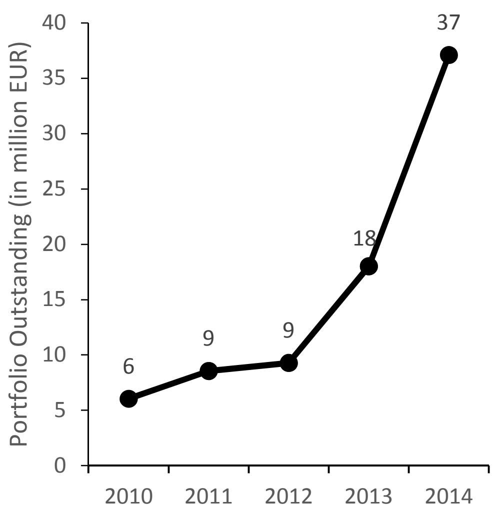
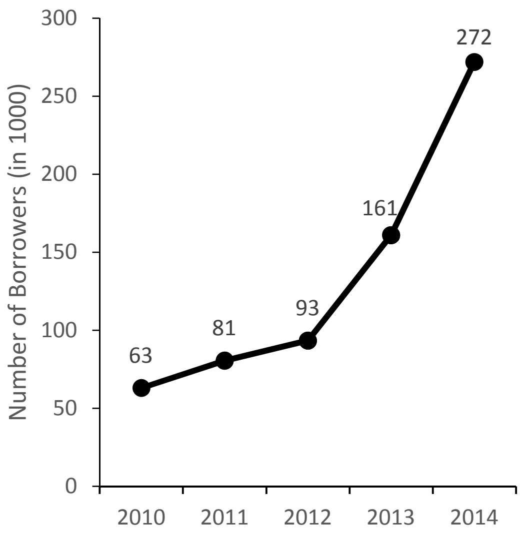


Figure 2: SVCL growth by number of borrowers

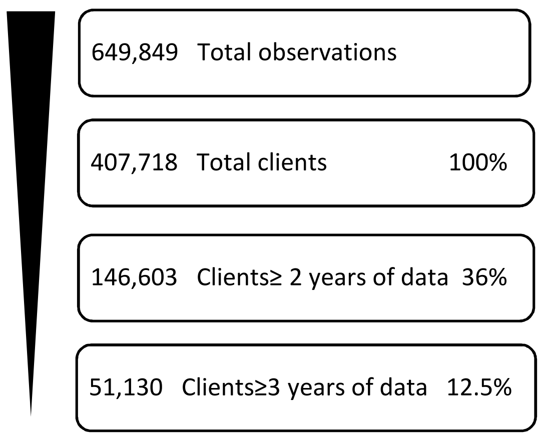


SVCL collects data on PPI as a part of a regular loan application process. Data is collected by loan officers who personally visit the clients' homes. The recorded information on borrowers which includes owned assets, household income, number of household members, credit history and other relevant information, is collected in the internal forms. The branch manager then needs to review these forms before data is entered into the MIS. While the official policy documents outline that 100% of the data needs to be crosschecked, in practice data errors were not always fed back to the loan officers. Furthermore, the data was not always properly stored: with the exception of the PPI, loan, and income indicators, most indicators (e.g. the client's occupation) were overwritten once clients renewed their loans and updated their profiles. This limits the fixed-effects model in capturing the influence of time-varying personal attributes (occupation, location etc.) on the SVCL clients' poverty levels.

By visiting a few SVCL client households, we found that the loan officers have a good understanding of the PPI scorecard, and were able to accurately communicate all 10 questions to the household members. Interviews carried out with a few selected loan officers also revealed that all PPI forms are completed at the loan applicant's home by duly verifying all household assets. We also did not notice any significant outliers in the PPI score data. Therefore, we conclude that the PPI data is appropriately recorded, and of good quality. Nevertheless, in conducting PPI surveys there is always a risk of translation bias, incomplete verification of household assets by loan officers, and quality control issues, among others, which can affect data quality. The data on loan indicators was reliable as it verified as a part of the financial audits conducted at SVCL. Annual income data is based on the estimation of the approximate monthly income of borrowers, and is therefore relatively less reliable. Data checking did not reveal any significant outliers for any indicator, therefore all observations were considered in the econometric analysis. Overall, we find the SVCL data to be of good quality.

For SVCL, we have an unbalanced panel dataset of 407,718 clients, totalling 649,844 observations over the period January 2010 to October 2014. Figure 3 indicates that around 36% of SVCL clients obtained microcredit for two or more years during the period 2010-2014. This suggests that we have a large yet unbalanced panel dataset, both in terms of the number of individuals and time, to analyse the short-term changes in poverty due to microfinance intervention.

Figure 3: Distribution of SVCL Data



The distribution of the PPI score was nearly normal. During the period 2010-14, the average PPI score declined from 47 to 45.8. Table 7 in the Annex suggests that the average poverty rate of clients who remained active from 2010 until 2014 decreased from 14.7% to 11.8%. In terms of products and services, SVCL predominately offers credit. The average loan borrowed per client increased from INR 9,859 in 2010 to INR 17,328 by 2014. Around 61.5% of clients have taken one loan from SVCL, and around 1.5% of the clients have taken more than five loans. During the period of study, SVCL offered a total of 11 loan products with interest rates varying from 26% to 32% and at a tenure of 46 or 104 weeks. Almost all clients are female with the majority living in urban areas.

Over the years, SVCL borrowers' participation has continuously declined in the agricultural, service and trading sectors. We observe 96% of SVCL clients were married.

Comparing SVCL poverty rates with India's official figures[6] suggests that SVCL target clients were around and above the poverty line. We also made a comparative analysis of SVCL poverty rates with average poverty rates of other Oikocredit partners in India. Data suggests that during 2013-14 the average poverty rate of Oikocredit's Indian partners decreased from 20.6% to 18.7% - in comparison, the poverty rate of SVCL clients decreased from 11.7% to 11.4%. We found a strong correlation (0.78) between the poverty rate of SVCL clients and India's official poverty rates for 2011-12 (see Table 7) indicating that the data is of sufficient quality.

Table 1: Descriptive Statistics of SVCL (Full Sample *n=649,844*)

Variable	Mean	Std. Dev.
Loan Amount	14,211	3,901
Annual Income	59,946	28,921
Loan Tenure	55.8	21.7
Loan Cycle	1.6	0.9
PPI Total Score	46.2	15.6
Poverty likelihood (as per NPL)	11.5	10.1
Borrower characteristics		
%Female clients	100	
%Divorced	0.2	
%Married	96.3	
%Single	0.2	
%Widowed	3.3	
%Rural clients	41.8	
%Urban clients	58.2	
% Agriculture	1.9	
% Animal Husbandry	3.5	
% Handicraft	6.8	
% Labour	48.3	
% Others	29	
% Rural Artisans	1.4	
% Service	1.2	
% Trade	7.9	

Note: for variables rural and urban n= 351,535

6 http://data.worldbank.org/country/india

Table 2: Descriptive Statistics of SVCL (Yearly Data)

Variable	2010	2011	2012	2013	2014
	Mean	Mean	Mean	Mean	Mean
Loan Amount	9,859	10,830	12,033	14,523	17,328
Annual Income	68,049	47,465	52,061	62,106	64,078
Loan Tenure	46	46	46	53.7	68.2
Loan Cycle	1	1.3	1.5	1.7	1.7
PPI Total Score	47	48	46.1	45.6	45.8
Poverty likelihood (as per NPL)	11.8	11.1	11.7	11.7	11.4
Borrower characteristics					
% Female clients	100	100	100	99.9	99.9
% Divorced	0.2	0.2	0.2	0.2	0.2
% Married	95.3	95.9	96.3	96.4	96.5
% Single	0.6	0.4	0.2	0.2	0.2
% Widowed	3.9	3.5	3.3	3.2	3.1
% Rural clients	41.8	43.5	48.6	No Data	No Data
% Urban clients	58.2	56.5	51.4	No Data	No Data
% Agriculture	3.2	2.6	2.2	1.7	1.4
% Animal Husbandry	4.2	4.4	4.8	3.4	2.6
% Handicraft	7.3	8.4	8.1	6.8	5.4
% Labour	38.1	40.7	45.6	50.1	53.5
% Others	30.8	27.6	25.8	28.3	30.9
% Rural Artisans	1.5	1.7	1.8	1.4	1.1
% Service	2.0	1.9	1.4	1.1	0.7
% Trade	12.9	12.7	10.4	7.2	4.4

3.2. ASKI Data

Alalay Sa Kaunlaran, Incorporated (ASKI) is a Philippines-based MFI providing microcredit, insurance and a variety of non-financial services to low-income households in the Philippines. Figure 4 and Figure 5 show that during 2011-14, ASKI's total loan portfolio increased by 25%, while the number of borrowers increased by 31%. Over the same period the company's mean annual retention rate has been around 71%[7].

[7] The annual retention rate of ASKI is calculated by: borrowers at the end of the period/ (borrowers at the beginning of the period + new borrowers entering during the period). Please note that a subsample of borrowers that changed branches (approx. 2% of the sample) received new client ID numbers and therefore retention rates may improve further after accounting for such clients.
For the purpose of this paper, for any period, we define the retention rate simply as the ratio of borrowers at the end of the period/ borrowers at the beginning of the period because we are interested in the long term customer retention.

Figure 4: ASKI growth by loan outstanding

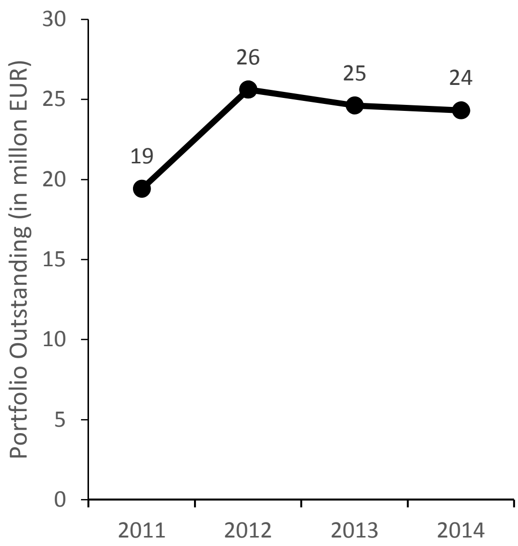
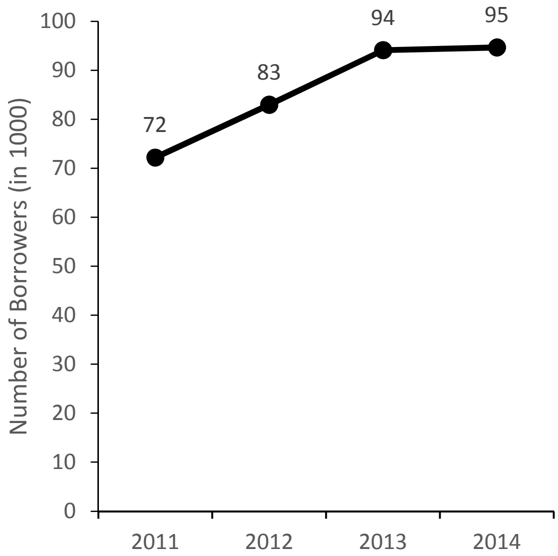


Figure 5: ASKI growth by number of borrowers

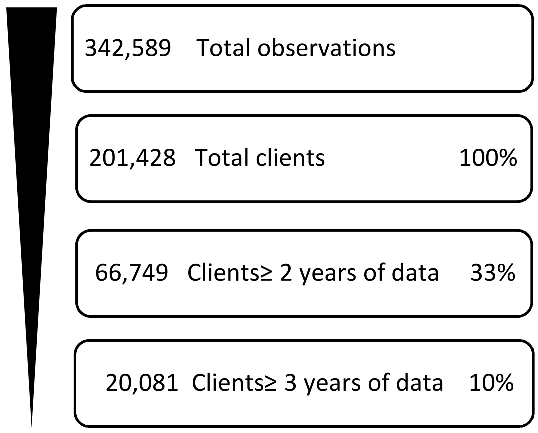


ASKI collects data on PPI as a part of its overall loan application and monitoring process. Data is collected by the loan officers who personally visit the client's home. The branch manager reviews the forms before entering the data into the MIS. Data is properly stored on a regular basis, implying that we have multiple time-varying indicators at our disposal. ASKI's research and development department regularly uses the PPI data for product development, mission tracking and operations. At the same time, staff and management recognized that there is scope for improvement, particularly in tracking poverty changes over time and cascading results throughout the organization. The company was PPI certified by the Grameen Foundation in 2011 and received an A- social rating from Microfinanza in December 2013.

Interviews with ASKI loan officers revealed that they had a good understanding of the PPI scorecard. The PPI data seemed to be recorded appropriately. We dropped observations for loan amounts less than PHP 3,000 as these pertain to insurance loans, and loan amounts of more than a million Philippine pesos, as these are unlikely. A few observations with loan tenures of more than 100 months were also dropped from the final analysis as ASKI does not offer such loans. For the remaining parameters, we do not notice any significant errors in the data. The final data utilized in the analysis is of good quality.

For ASKI, we have an unbalanced dataset of 201,428 clients, totalling 342,589 observations over the period 2011-2014. Figure 6 suggests that around 33% of ASKI clients have borrowed microcredit for two or more years. For example, out of the 72,240 clients receiving new loans in ASKI in the year 2011, 36,948 (51%) remained active borrowers after January 2013, 15.231 (21%) remained active after January 2014 and 3.840 remained active after January 2015 (see Table 9 in the Annex). Thus we have a large unbalanced panel dataset for ASKI for several years to analyse the short-term changes in poverty due to microfinance intervention.

Figure 6: Distribution of ASKI Data



The distribution of the data on the PPI score was nearly normal. As shown in Table 4 the average PPI score of ASKI clients increased from 57.4 in 2011 to 59.7 in 2014, implying that the average poverty rate decreased from 17.1% in 2011, to 15.1% in 2014. The average poverty rate of clients who remained active from 2011 until January 2015 reduced slightly more from 13.3% to 10.3% (see Table 9 in Annex). The average loan per client increased from PHP 15,271 in 2011 to PHP 15,933 in 2014. Around 38% of clients in the sample have taken only one loan from ASKI. During the period of study, ASKI offered nine different loan products (group & individual) at an annual interest rate ranging from 0% to 36%. In 2011, all loans were disbursed with a tenure of six months, and thereafter the loan tenure varied from 1 to 84 months.

The proportion of female clients in ASKI increased marginally from 74% in 2011 to 77.5% in 2014 and the percentage rural clients increased from 85% to 88% during the same period. Participation levels among ASKI borrowers declined in the agriculture, manufacturing, and professional job sectors, and increased in the trading and service sectors. Around 82% of ASKI clients were married.

The correlation between ASKI poverty rates and official Philippines poverty lines for 2012 is weak (0.50) See Table 10 in the Annex). The poverty outreach of ASKI borrowers decreased from 17.1% in 2011 to 15.1% in 2014 (-2%). According to Oikocredit poverty outreach benchmarking data on Philippine MFIs, the poverty rate among MFI clients in the Philippines decreased from 25.1% in 2013 to 22.6% in 2014 (-2.5%).

Table 3: ASKI Descriptive Statistics (Full Sample, n=358,532)

Variable	Mean	Std. Dev.
Loan Amount	15,962	19,368
Loan Tenure	6.2	1.942
Loan Cycle	1.6	0.5
PPI Score	58.6	16.5
Poverty Likelihood (as per NPL)	15.9	20.2
Borrower characteristics		
%Female clients	74.5	
%Married	82	
%Separated	1.4	
%Single	13.3	
%Widowed	3.3	
%Rural clients	84.9	
%Urban clients	15.1	
%Agriculture	22.5	
%Employee	0.9	
%Manufacturing	3	
%Others	8.1	
%Services	9.5	
%Trading	56	

Note: For variables marital status and rural, n=286,954 obs.

Table 4: ASKI Descriptive Statistics (Yearly Data)

Variable	2011	2012	2013	2014
	Mean	Mean	Mean	Mean
Loan Amount	15,271	16,629	15,675	15,933
Loan Tenure	6	6.3	6.2	6.4
Loan Cycle	1.5	1.7	1.6	1.7
PPI Score	57.4	60	57.4	59.7
Poverty Likelihood (National Poverty line)	17.1	14.5	17.1	15.1
Borrower characteristics				
% Female clients	73.9	73.6	74.6	77.5
% Married	No data	83.3	81.2	80
% Separated	No data	1.3	1.5	1.9
% Single	No data	12.4	14	14.2
% Widowed	No data	3	3.3	3.9
% Rural clients	85.1	83.6	84.7	88.1
% Urban clients	14.9	16.4	15.3	11.9
% Agriculture	23.9	25.3	22.1	14.1
% Employee	0.0	0.5	1.3	2.1
% Manufacturing	3.4	3.0	2.6	3.2
% Others	7.8	7.0	8.2	10.9
% Services	10.3	9.2	8.7	11.2
% Trading	54.6	54.9	57.2	58.6

4. Methodology

The data at hand allows us to estimate fixed- effects OLS regression model to examine the average effect of microcredit on poverty of a borrower. Secondly, we construct a pooled OLS model that pools data at the individual level to study more closely the cross sectional variability in the poverty outreach data and examine the factors influencing it. The pooled model is estimated because we deal with highly unbalanced panel datasets that also contain time-constant variables that may still hold explanatory power on poverty variation but are cancelled in fixed effects modelling as the regression coefficients are estimated at the individual level. Both models assume a linear regression, leaving all second-order effects in the error term. The model for pooled OLS regression is given below.

$$\boldsymbol{Yit = \beta Xit + \theta Zit + YT + \alpha i + Uit} \quad \text{---}\mathbf{(1)}$$

Where Y is the PPI score of a microcredit borrower i at time t. Explanatory variables are considered based on past research studying the impact of microfinance on poverty, and the choice is also constrained by the availability of data from the MFI. X is a vector of time-varying individual characteristics. This vector includes the loan amount, loan tenure, loan cycle and income of an individual. Z is a dummy variable for individual characteristics including gender, occupation, marital status and location (rural/urban). To see the effect of time on poverty, year dummy variable (T) has also been used. The coefficients of interest in the model are β and θ. The OLS estimate of β and θ for pooled OLS gives the variability of poverty within the sample. The coefficient ϒ estimates the time effect in the model. Coefficient α_i is the intercept, and u_{it} represents the idiosyncratic errors, which varies across individuals and time.

The pooled OLS is a highly restrictive model, as it assumes no correlation of observed individual characteristics with unobserved heterogeneity and idiosyncratic errors (Woolridge, 2002:256), and also ignores the panel characteristics of the data. Since this method does not control for unobserved heterogeneities, we estimate a fixed-effects model.

The advantage of using a fixed-effects model is that it controls for relevant unobserved characteristics that do not change over time (Lensink and Pham 2008). The fixed-effects model also allows observed characteristics to be arbitrarily correlated with unobserved fixed effects resulting in robust estimates, however, this comes at a price that time-constant individual factors such as gender cannot be included in $\mathbf{X_{it}}$ (Woolridge, 2002:266). Also, although the fixed-effect model controls the unobserved time-invariant attributes, it does not entirely tackle the endogeneity problem, as some unobserved attributes may change over time (Khandekar 2005).

The time demeaning of equation 2 gives us the fixed-effects model.

$$\ddot{Y}\boldsymbol{it = \beta}\ddot{X}\boldsymbol{it + \theta}\hat{Z}\boldsymbol{it + YT +} \ddot{u}\boldsymbol{it} \quad \text{---}\mathbf{(2)}$$

Where Ÿ, Ẍ, and Ẑ are the same variables as explained for the pooled model, but are time demeaned to control for unobserved individual characteristics. The coefficients of interest in the fixed-effects model are β and θ. The OLS estimate of β and θ in this method gives the average effect of relevant variables on the poverty of borrowers. The coefficient ϒ estimates the time effect in the model. All variances in both models are white-corrected using robust standard errors.

Regression results are first analysed by running the models with loan amount as the main explanatory variable while controlling for various client related characteristics available for SVCL and ASKI borrowers. We then conduct sensitivity analysis by testing regression results for individuals who have taken three or more loans, four or more loans and five or more loans.

A word of caution on the evaluation of the loan effect needs to be made beforehand to ensure a proper interpretation and understanding of the limitations of the model. We estimate average loan effects controlling for other indicators available in the MFI datasets. The measured effects are not impact estimations because we do not have a control group of people who did not receive microcredit. Secondly, we demonstrate analysis of data for the MFI's active portfolio and do not have information on clients as to when they exited the program. Thus, we are unable to control for selection and attrition bias in the sample. Thirdly, the regressions control for measurable indicators and in doing so, the model assumes that these indicators are not highly correlated with other unobserved indicators that influence poverty. Particularly unobservable indicators that are subject to change can cause challenges in the econometric analysis. We conducted a substantial sensitivity analysis on subsamples of data to test the robustness of the changes in the loan estimator.

To translate the effect of microfinance on PPI score to poverty likelihood, we establish a parsimonious linear relationship between poverty likelihood and PPI score. The poverty look-up tables published by the Grameen Foundation do not allow researchers to track poverty likelihood for small changes in the PPI score (e.g. 1-4 units). Our econometric analysis suggests a very small variability in the PPI score due to microfinance, and we are interested in interpreting the results in terms of poverty likelihood. To do so, we utilize the data on PPI score and poverty likelihood from the poverty look-up tables to construct a mathematical function that best describes the continuous relationship between PPI score and poverty likelihood. While doing so, we do not alter the basic mathematical function used by the Grameen foundation to describe the relationship between PPI score and poverty likelihood for India and Philippines. The mathematical relationship between the poverty likelihood (as per national poverty line) and PPI score is described in Equation 3 for India and Equation 4 for Philippines. We use these equations to translate the regression coefficients of pooled OLS and fixed effects (indicating the effect of an explanatory variable on PPI score) into changes in poverty likelihood. Figure 7 and Figure 8 graphically demonstrate the PPI score and poverty likelihood relationship. Poverty likelihood used in the equations below is linked to the national poverty line of India and the Philippines and is used in the construction of the relevant version of poverty look-up tables by the Grameen Foundation.

We use the national poverty lines to interpret the effect, because we aim to track poverty changes within the country, and not make cross-country comparisons. Secondly, since national poverty lines are defined according to the specific social and economic circumstances of each country, they give a more realistic and accurate number on poverty. It is worth indicating that the equations below are derived for India and the Philippines for the national poverty line in the versions of PPI scorecard used by SVCL and ASKI. The equations are country specific, and will change with poverty lines (e.g. national, international, US AID) and the version of the PPI scorecard. [8]

$$\boldsymbol{Poverty\ Likelihood\ (India)\ =\ exp(\ -0.0495 * PPI\ +\ 4.404)} \text{------------------------------} \textbf{(3)}$$

$$\boldsymbol{Poverty\ Likelihood\ (Philippines)\ =\ \ 100/\ (1+\ exp(0.1251 * PPI\ -4.1894)} \text{------} \textbf{(4)}$$

[8] For example, if a client in India has a PPI score of 20, as per equation (3) his/her poverty likelihood will be 30.4%. This is different from the 28.7% poverty likelihood figure calculated by the Grameen Foundation, but does not our results, because we are primarily interested in tracking changes in poverty, rather than the absolute figures.

Figure 7:PPI Score and Poverty Likelihood Graph (India)

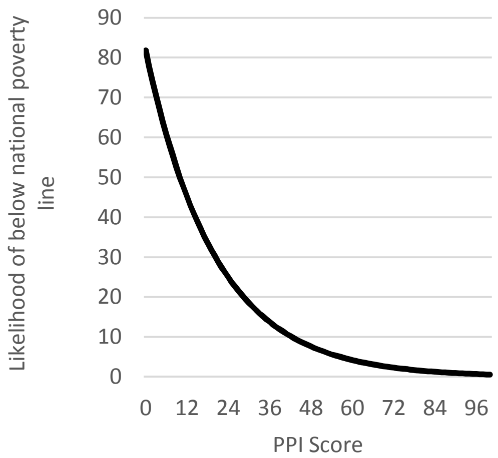
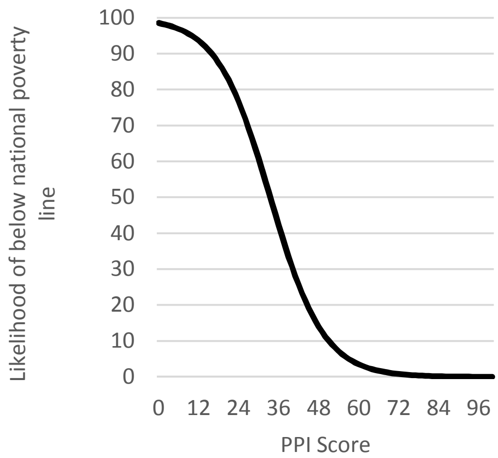


Figure 8: PPI Score and Poverty Likelihood Graph (Philippines)



5. Results

5.1. Influence of microfinance on the poverty of SVCL clients

Fixed effects model

The overall results suggest that microfinance loans have a significant positive effect on the poverty of SVCL borrowers. Econometric analysis suggests that for every INR 10,000 increase in the loan amount, the PPI score increases by 0.6 units on average. For SVCL, Equation (3) can then be used to translate the PPI scores into poverty likelihoods. As an example, if an SVCL client has a PPI score of 20, an additional loan of INR 10,000 would increase his/her PPI score to 20.6 (+0.6), which corresponds to a reduction of poverty likelihood from 30.4% to 29.5% (-0.9%). Another example, if an average SVCL client has a PPI score of 46.1, an additional loan of INR 10,000 would increase his/her PPI score to 46.7 (+0.6), which corresponds to a reduction of poverty likelihood from 8.3% to 8.1% (-0.2%). This implies that the overall effect of microcredit on poverty likelihood of a borrower is marginal and statistically significant.

The result for the loan cycle suggests that for each extra loan the PPI score increases, implying a reduction in poverty likelihood. The time-effect on poverty shows that compared to 2010, the poverty likelihood of an SVCL borrower was lower in 2011, 2012, 2013 and 2014. Sensitivity analysis demonstrates that for every INR 10,000 increase in loan amount the change in PPI score varies positively between 0.6 and 1.1. We therefore conclude that microfinance had a positive effect on the poverty of SVCL clients.

Table 5: Result of Fixed-Effects Model (SVCL)

Explanatory Variables	Main Model 2 or more loans	3 or more loans	4 or more loans	5 or more loans
	PPI Score	PPI Score	PPI Score	PPI Score
Loan Amount (in INR 10,000)	0.604***	1.081***	0.939**	0.851
	(0.155)	(0.205)	(0.321)	(0.555)
Year2011	2.478***	2.398***	2.635***	3.927***
	(0.123)	(0.157)	(0.212)	(0.343)
Year2012	2.536***	2.650***	3.376***	5.227***
	(0.197)	(0.249)	(0.363)	(0.637)
Year2013	2.003***	2.450***	3.216***	5.634***
	(0.271)	(0.350)	(0.520)	(0.915)
Year2014	1.914***	2.170***	2.600***	5.506***
	(0.330)	(0.437)	(0.658)	(1.143)
Tenure	-0.00699**	-0.0180***	-0.0151***	-0.00695
	(0.00216)	(0.00285)	(0.00451)	(0.00800)
Loan Cycle	0.405***	0.193	-0.0324	-0.907**
	(0.0947)	(0.121)	(0.177)	(0.296)
Income (in INR 10,000)	0.140***	0.140***	0.117***	0.119***
	(0.0103)	(0.0125)	(0.0161)	(0.0240)
Intercept	42.30***	41.56***	41.66***	42.38***
	(0.184)	(0.183)	(0.244)	(0.425)
Number of observations	649,755	199,162	91,302	34,676
R-sq	0.0071	0.0078	0.0108	0.0145
F	213.3	136.6	95.45	56.68
Number of clients	407,670	56,949	20,992	6,835

Standard errors in parentheses

*** p<0.001 ** p<0.01 * p<0.05 + p<0.10

Pooled OLS model

A relevant question for this discussion paper is what type of clients are generally poorer. We ran a pooled regression estimation for SVCL at client level and found that access to higher microfinance loans and higher income are associated with a decrease in poverty likelihood (see Table 11 in the Annex). We observe a significant effect of marital status, occupation and location of clients on the poverty levels of individuals. Findings suggest that women working in rural areas are more likely to be poor than those in urban areas. Borrowers employed in the agricultural sector and working as labours, are more likely to be poor. Interestingly, we find single women are less likely to be poor than married and male clients. Sensitivity analysis on the pooled OLS model does not reveal any significant changes in the positive or negative direction of the coefficients of loan amount. We therefore find the original pooled OLS model to be quite robust.

5.2. Influence of microfinance on the poverty of ASKI clients

Fixed effects model

The overall results suggest that microcredit has a significant positive effect on the poverty of ASKI borrowers. Econometric analysis suggests that for every PHP 10,000 increase in the loan amount, on average, the PPI score on an individual increases by 0.5 units. For ASKI, Equation (4) can then be used to translate the PPI scores into poverty likelihoods. For example, if an ASKI client has a PPI score of 20, an additional loan of PHP 10,000 would increase his PPI score to 20.5 (+0.5), which corresponds to a reduction of poverty likelihood from 84.4% to 83.5% (-0.9%). Likewise, for an ASKI client with an average PPI score of 58.6, an additional loan of PHP 10,000 would increase his PPI score to 59.1 (+0.5), which corresponds to a reduction of poverty likelihood from 4.14% to 3.90% (-0.2%).

Fixed effect regression analysis also indicates that few clients have migrated from rural to urban areas or vice versa, and clients who moved to rural areas have become poorer than when they were located in urban areas. OLS estimate of occupation shows that changing occupation from agriculture to trading reduces the poverty likelihood among ASKI borrowers. The time effect on poverty demonstrates that, when compared to 2011, the poverty likelihood of ASKI borrowers was lower in 2012, 2013 and 2014. Results of the sensitivity analysis suggest that for every PHP 10,000 increase in the loan amount the change in PPI score varies positively between 0.441 and 0.505. We therefore conclude that microfinance had a positive effect on poverty among ASKI clients.

Table 6: Results of Fixed-Effects Model (ASKI)

	Main Model PPI Score	3 or more loans PPI Score	4 or more loans PPI Score	5 or more loans PPI Score
Loan Amount(in PHP 10,000)	0.505***	0.457***	0.488***	0.441***
	(0.0385)	(0.0436)	(0.0559)	(0.0836)
Year2012	2.049***	1.822***	1.520***	1.414***
	(0.101)	(0.119)	(0.150)	(0.200)
Year2013	1.102***	0.941***	0.741***	0.812***
	(0.115)	(0.133)	(0.163)	(0.218)
Year2014	3.267***	3.073***	3.013***	3.185***
	(0.143)	(0.165)	(0.199)	(0.258)
Tenure	-0.122***	-0.109***	-0.0975*	-0.0928
	(0.0264)	(0.0325)	(0.0452)	(0.0591)
Loan Cycle (=Renewal)	-0.159*	0.226*	0.482**	0.654*
	(0.0618)	(0.0991)	(0.155)	(0.276)
Location (=Rural)	-0.403**	-0.174	0.0340	0.389
	(0.154)	(0.175)	(0.230)	(0.350)
Occupation(=Employee)	-0.152	-0.418	-1.256	0.403
	(0.508)	(0.658)	(1.072)	(1.987)
Occupation (=Manufacturing)	-0.301	-0.0617	0.417	1.272*
	(0.308)	(0.359)	(0.432)	(0.551)
Occupation(=Others)	0.224	0.371+	0.410	0.425
	(0.194)	(0.221)	(0.266)	(0.360)
Occupation(=Services)	-0.0119	-0.0232	0.317	0.628
	(0.228)	(0.263)	(0.320)	(0.432)
Occupation (=Trading)	0.305+	0.281	0.348	0.480
	(0.176)	(0.200)	(0.238)	(0.313)
Intercept	56.94***	57.19***	57.21***	57.45***
	(0.256)	(0.300)	(0.402)	(0.571)
Number of observations	327,242	144,535	81,350	40,535
R-sq	0.0114	0.0101	0.0100	0.0114
F	99.03	64.41	41.01	24.74
Number of clients	187,491	42,448	19,291	8,245

Standard errors in parentheses

*** p<0.001 ** p<0.01 * p<0.05 + p<0.10

Pooled OLS model

What type of clients are generally poorer? We ran a pooled regression estimation for ASKI at client level and found that access to higher microfinance loans is associated with a reduction in poverty likelihood (see Table 12). The findings demonstrate that clients working in rural areas are more likely to be poor than those living in urban areas. Borrowers employed in the agricultural sector are more likely to be poor when compared to those employed in other sectors. We find single women are less likely to be poor than married clients. The sensitivity analysis of the pooled OLS model does not reveal any significant changes in the coefficient of loan amount and we therefore find the pooled OLS model to be quite robust.

6. Conclusions

This paper examined the effect of microcredit on poverty by using client level unbalanced panel data for two leading MFIs: SVCL, India and ASKI, Philippines. In total, we analysed more than a million poverty records, for roughly 600,000 microcredit borrowers, over a period of four years. We used fixed-effects regression to assess the effect of microcredit on the poverty of borrowers, and pooled OLS model to check cross-sectional factors influencing the variability in poverty. In doing so the study used the PPI score, an asset-based indicator of poverty, as the dependent variable in the econometric analysis. The effect of microcredit is evaluated by using the loan amount as the main explanatory variable, while controlling for time-varying variables (income, loan tenure, loan cycle, occupation, and location) and time-constant observed (gender, marital status) and unobserved individual attributes.

Acknowledging the limitations of the data and the model, our empirical analysis demonstrates that microcredit has a small positive and significant effect on poverty reduction for borrowers for both SVCL in India and ASKI in the Philippines. The data further illustrated that income, occupation and the location (rural/urban) of microcredit borrowers also have significant effects on poverty.

Although the methodology deployed is limited in terms of impact measurement, we believe it adds significant value because by using readily available monitoring data the analysis can be carried out in a much more cost-effective manner. We estimate the costs to be around € 20,000-25,000 per MFI, which includes the offering of capacity building support to the MFI staff in analysing and utilizing data, as well as the development and analysis of the generic econometric model. A second advantage is that large sample sizes allow breakdowns of estimates for sub-samples of data. Further analysis can be conducted to evaluate poverty effects over time for specific sub-groups of borrowers. Finally, this method can be replicated easily into other MFIs, provided that they have good quality client-outcome data available. Similar studies could be conducted - not just for PPI but also for other poverty or employment indicators.

Throughout the project implementation we made interesting findings: while the PPI can potentially be used to track changes in client lives over time, the MFIs did not utilize their data to its full potential. We noticed that MFI staff and management were highly interested in understanding clients' poverty changes, however, their information systems generally were geared towards measuring poverty outreach rather than capturing that change. We also recommend that PPI indicators be better selected to their sensitivity to timely changes. Furthermore given that changes in poverty are generally small, poverty look-up tables should show smaller intervals so that MFIs can actually use them to document changes in clients' lives. We advise MFIs to supplement PPI data with other client-outcome data and to store it on a timely basis as panel data. In the absence of a control group, MFIs could incorporate additional indicators into their MIS systems that help link credit intervention to poverty outcomes, for example by documenting whether clients utilize loans for productive purposes. Strong client attrition for both MFIs demonstrates that microcredit may not be a long-term intervention. Therefore collecting PPI survey data during customer exit interviews would provide valuable insights as to whether poverty reduction is more sustainable.

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Annex I: Data Summary

Table 7 shows the poverty likelihood for clients who joined SVCL in 2010 and remained active for different durations. Column one shows the dates for which the clients remained active with SVCL. Column two lists the number of clients. Columns three to seven present the average poverty likelihood for these clients.

Table 7: SVCL over time poverty rate for different client samples joining in 2010

Sub-sample	Nr of Clients	Poverty rate (NPL)				
		2010	2011	2012	2013	2014
Clients joining in 2010	59,250	11.8	-	-	-	-
Of whom remained active after Jan 2012	23,748	12.7	10.8	-	-	-
remained active after Jan 2013	12,388	13.7	11.8	11.2	-	-
remained active after Jan 2014	8,431	14.2	12.1	11.6	11.4	-
remained active after Jan 2015	4,952	14.7	12.4	11.8	11.7	11.8

Table 8 correlates the state poverty of SVCL clients with the official poverty data for Indian states. Column two shows that overall SVCL poverty data and official Indian poverty data has a correlation coefficient of 0.78. Column three or seven show the correlation coefficient of yearly SVCL poverty data and official Indian poverty rates.

Table 8: Comparing SVCL and India poverty rates (2011-2012) [9]

	SVCL Poverty Rates	2010	2011	2012	2013	2014
Correlation Coefficients	0.780	0.439	0.599	0.806	0.842	0.880

Table 9 shows the poverty likelihood for clients who joined ASKI in 2011 and remained active for different durations. Column one shows the dates for which the clients remained active with ASKI. Column two lists the number of these clients. Columns three to seven present the average poverty likelihood of the active clients.

Table 9: ASKI over time poverty rate for different client samples

Sub-sample	Nr of clients	Poverty rate (NPL)			
		2011	2012	2013	2014
Clients joining in jan- dec 2011	72,240	17.1	-	-	-
Of whom remained active after Jan 2013	36,948	16.7	14.4	-	-
remained active after Jan 2014	15,231	15.7	13.6	14.3	-
remained active after Jan 2015	3,840	13.3	12.1	12.1	10.3

[9] http://planningcommission.gov.in/data/datatable/data_2312/DatabookDec2014%20101.pdf

Table 10 correlates the province poverty of ASKI clients with the official poverty data for Philippine provinces. Column two shows that overall ASKI poverty data and official Philippines poverty data has a correlation coefficient of 0.501. Column three or six shows the correlation coefficient of yearly ASKI poverty data and official Philippines poverty rates.

Table 10 Comparing ASKI and Philippines poverty rates

	Overall	2011	2012	2013	2014
Correlation	0.501	0.116	0.548	0.596	0.689

Annex 2: Pooled OLS Regression Results

Table 11 reports the results of the pooled OLS regression model for SVCL clients. Column one displays the independent variables. Column two shows regression coefficients and other regression results for the complete sample. Column three for clients who have taken two or more loans. Column four for clients who have taken three or more loans. Column five for clients who have taken four or more loans. Column six for clients who have taken five or more loans. All variances are white-corrected using robust standard errors.

Table 11: Results of Pooled OLS Model (SVCL)

Explanatory Variables	Main Model	2 or more loans	3 or more loans	4 or more loans	5 or more loans
	PPI Score	PPI Score	PPI Score	PPI Score	PPI Score
Loan Amount (in INR 10,000)	10.07***	9.438***	8.688***	8.757***	8.801***
	(0.162)	(0.175)	(0.195)	(0.305)	(0.529)
Year2011	1.348***	1.851***	2.184***	2.294***	1.963***
	(0.0890)	(0.126)	(0.162)	(0.202)	(0.369)
Year2012	-1.052***	-0.202+	0.837***	0.813***	0.276
	(0.0877)	(0.122)	(0.156)	(0.237)	(0.567)
Year2013	-3.156***	-2.232***	-1.070***	-1.035***	-1.948*
	(0.119)	(0.144)	(0.178)	(0.294)	(0.786)
Year2014	-5.344***	-4.578***	-3.479***	-4.643***	-5.860***
	(0.170)	(0.190)	(0.223)	(0.373)	(0.967)
Tenure	-0.0861***	-0.0821***	-0.0732***	-0.0661***	-0.0664***
	(0.00259)	(0.00269)	(0.00307)	(0.00479)	(0.00849)
Loan Cycle	-0.950***	-0.548***	-0.409***	-0.121	0.111
	(0.0412)	(0.0427)	(0.0476)	(0.0891)	(0.241)
Income (in INR 10,000)	0.374***	0.482***	0.542***	0.534***	0.429***
	(0.00861)	(0.0123)	(0.0151)	(0.0222)	(0.0341)
Location(=Urban)	7.124***	6.634***	6.125***	5.698***	6.325***
	(0.0539)	(0.0622)	(0.0721)	(0.105)	(0.172)
Occupation (=Animal Husbandry)	4.406***	3.758***	2.912***	1.744***	1.493*
	(0.201)	(0.232)	(0.271)	(0.387)	(0.668)
Occupation (=Handicraft)	8.113***	6.779***	5.900***	5.136***	4.013***
	(0.187)	(0.218)	(0.254)	(0.368)	(0.654)
Occupation (=Labour)	-1.975***	-2.370***	-2.527***	-2.839***	-2.528***
	(0.165)	(0.191)	(0.223)	(0.311)	(0.559)
Occupation (=Others)	4.173***	3.467***	3.364***	4.771***	5.409***
	(0.168)	(0.195)	(0.228)	(0.320)	(0.572)
Occupation (=Rural Artisans)	1.203***	0.600*	0.510+	0.568	0.648
	(0.234)	(0.262)	(0.298)	(0.426)	(0.735)
Occupation (=Service)	10.69***	9.112***	7.878***	8.303***	8.160***
	(0.268)	(0.320)	(0.370)	(0.529)	(0.914)
Occupation (=Trade)	3.801***	2.805***	2.224***	2.927***	3.575***
	(0.179)	(0.207)	(0.240)	(0.331)	(0.584)
Gender (=Female)	0	0	0	0	0

	(.)	(.)	(.)	(.)	(.)
Marital Status (=Divorced)	5.610***	5.352***	5.910***	6.562***	10.06**
	(0.742)	(0.879)	(1.026)	(1.480)	(3.211)
Marital Status(=Married)	-1.010*	-1.008+	-0.792	-1.222	0.206
	(0.444)	(0.545)	(0.653)	(0.769)	(1.066)
Marital Status(=Widowed)	3.190***	3.009***	3.153***	3.001***	3.914***
	(0.464)	(0.568)	(0.679)	(0.815)	(1.148)
Intercept	34.14***	33.13***	32.09***	30.97***	29.01***
	(0.489)	(0.597)	(0.716)	(0.872)	(1.283)
N	351,446	266,563	195,477	91,298	34,676
R-sq	0.1492	0.1390	0.1306	0.1378	0.1375
F	3324.5	2280.7	1548.1	757.1	292.3

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Table 12 reports the results of the pooled OLS regression model for ASKI clients. Column one displays the independent variables. Column two shows regression coefficients and other regression results for the complete sample. Column three for clients who have taken two or more loans. Column four for clients who have taken three or more loans. Column five for clients who have taken four or more loans. Column six for clients who have taken five or more loans. All variances are white-corrected using robust standard errors.

Table 12: Results of Pooled OLS Model (ASKI)

Explanatory Variables	Main Model	2 or more loans	3 or more loans	4 or more loans	5 or more loans
	PPI Score	PPI Score	PPI Score	PPI Score	PPI Score
Loan Amount(in PHP 10,000)	2.145***	2.114***	2.216***	2.381***	2.459***
	(0.0612)	(0.0731)	(0.0782)	(0.0586)	(0.0678)
Year2012	2.516***	1.915***	1.205***	1.337***	-1.668***
	(0.0650)	(0.0734)	(0.0919)	(0.122)	(0.251)
Year2013	0	0	0	0	-2.906***
	(.)	(.)	(.)	(.)	(0.249)
Year2014	1.766***	2.076***	2.452***	2.763***	0
	(0.0856)	(0.126)	(0.155)	(0.192)	(.)
Tenure	0.254***	0.227***	0.101**	-0.0861+	-0.282***
	(0.0235)	(0.0331)	(0.0360)	(0.0487)	(0.0766)
Loan Cycle (=Renewal)	0.327***	-0.164	0.216	0.836***	0.860+
	(0.0751)	(0.101)	(0.151)	(0.238)	(0.443)
Location (=Rural)	-1.403***	-1.210***	-1.199***	-1.126***	-0.905***
	(0.0785)	(0.0906)	(0.109)	(0.146)	(0.209)
Occupation(=Employee)	11.48***	12.35***	12.98***	14.34***	16.37***
	(0.299)	(0.398)	(0.526)	(0.828)	(1.264)
Occupation (=Manufacturing)	4.103***	3.956***	4.283***	5.362***	6.535***
	(0.196)	(0.226)	(0.272)	(0.342)	(0.476)
Occupation(=Others)	2.868***	1.773***	0.966***	0.383	0.404
	(0.158)	(0.194)	(0.234)	(0.275)	(0.383)

Occupation(=Services)	4.769***	4.910***	5.533***	6.403***	6.927***
	(0.141)	(0.171)	(0.200)	(0.228)	(0.309)
Occupation (=Trading)	4.726***	4.932***	5.335***	6.129***	6.886***
	(0.111)	(0.133)	(0.148)	(0.165)	(0.231)
Gender (=Female)	0.463***	0.569***	0.899***	0.946***	1.511***
	(0.0766)	(0.0916)	(0.114)	(0.149)	(0.215)
Marital Status(=Married)	-3.248***	-3.334***	-2.843***	-2.785***	-2.874***
	(0.0880)	(0.111)	(0.149)	(0.207)	(0.315)
Marital Status (=Separated)	0.0352	0.0749	0.771+	1.779***	1.217+
	(0.249)	(0.314)	(0.409)	(0.522)	(0.722)
Marital Status (=Widowed)	-0.0335	-0.101	0.158	0.241	0.183
	(0.178)	(0.209)	(0.258)	(0.331)	(0.460)
Intercept	52.18***	52.88***	52.60***	52.41***	55.93***
	(0.181)	(0.230)	(0.309)	(0.453)	(0.783)
N	285,675	202,798	129,277	72,804	35,988
R-sq	0.0881	0.0882	0.0923	0.1010	0.1074
F	701.4	469.7	298.7	268.2	183.0

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10