Final Report

Counting the (net) number of people who crossed (from below) the USD 1.25 a day consumption threshold in India between 1990 and 2010[1]

A Study by India Development Foundation, February 2011

[1] A presentation based on the preliminary findings was made on 17th November 2010. Subsequently, a draft report was submitted on 22nd March 2011. This final report incorporates comments and suggestions made in the Expert Panel meeting as well as by several members of the Advisory Panel following a teleconference on 25th March 2011. The authors wish to thank Awadhesh Kumar Jha, the members of the Expert Panel as well as the Advisory Panel for their valuable inputs. Special thanks are due to all the participating MFIs for sharing their valuable resources for the study.

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Executive Summary :

This study estimates how many continuing MFI clients in India have crossed the USD 1.25 PPP (per capita) a day consumption threshold from below. The time period considered for our study is 1990-2010. We find that, at an all India level, (approximately) a net of 12% ((9 million) of all MFI clients have crossed the USD 1.25 a day consumption threshold from below.

To arrive at the all India level estimate, we first divide the country into 6 distinct regions (North, South, East, West, Central and North East). We then identified the top 14 states whose MFI clientele is at least 1% or more of the all India total. These 14 states together have approximately 95% of the total MFI clientele in India. Thus the states are fairly representative of all the MFI clientele in India.

MFIs in India are not homogenous. Significant differences exist across MFIs either because they have different organizational structure or they practise different lending models. Therefore, the MFIs are classified into 9 cells. Each cell is a combination of a loan type (joint liability, individual liability or self help group) with any one of the three organizational types (NGO, NBFC, others). For each of the states, MFIs were identified belonging to each cell. There were 18 cells considered for each State-9 in rural and 9 in urban. There were 27 MFIs and 6 SHG Bank linked NGOs who participated in the study. The two most populous cells are NGO-SHG and NBFC-JLG combination.

Households were selected randomly from the clients list of the MFIs and surveyed. We surveyed 15,205 households. However, after omitting the missing observations, we were left with 14,746 households in all. The household questionnaire captured the current asset distribution as well as the asset distribution at the time of their joining the specific MFI. The latter was found out using the recall method.

The estimates were obtained by scoring the population from the collected data. Different scorecards for rural and urban households were developed for each of the 14 States. These scores are calibrated to the person's likelihood of being above or below a given consumption threshold.

Once the estimates for each cell were obtained, the population estimates were arrived at by using the population for each cell as the multipliers. We used the Statistical package Strata 8.E for the entire analysis.

Our key results are summarized below:

- At an all India level, (approximately) a net of 12% (9 million) of all MFI clients (74 million) have crossed the USD 1.25 a day consumption threshold from below.

- At an all India level, (approximately) one third of all MFI clients who started as 'poor' (below the USD 1.25 a day consumption threshold) have crossed the USD 1.25 a day consumption threshold from below. At an all India level, a net of 12% percent of all NGO clients crossed the threshold from below.
- At an all India level, a net of 12% percent of all NBFC clients crossed the threshold from below.
- At an all India level, a net of 12% percent of all NGO –SHG clients crossed the threshold from below.
- At an all India level, a net of 10% percent of all NBFC-JLG clients crossed the threshold from below.
- At an all India level, a net of 12% percent of all SHG Bank linkaged clients crossed the threshold from below.
- At an all India level, 37% of clients were poor (below the USD 1.25 a day consumption threshold) when they joined.
- At an all India level, the percentage of clients who were poor before joining the SHGs stand at 41%
- The percentage of clients who were poor when they joined is much higher in rural areas (40%) as against urban areas (25%)
- The movement is highest for clients those are associated between 4-6 years with the MFI

Chapter 1: Introduction

1.1 Introduction

For a country that has over 1.2 billion individuals and approximately 240 million households, less than half of the total households are financially included. For this half, who have no access to formal financial or banking accounts, Micro Finance Institutions (MFIs) play an important role. In India, MFIs have a widespread reach. There are more than 86 million MFI clients (Srinivasan, 2010). Around 60 million of these clients are served by NGO-SHGs that are linked to banks. The remaining 27 million clients are served by various organization and lending types. While the growth outreach of the NGO-SHG programme in 2009-10 was 8.5%, the growth outreach of other MFIs during this period was 18%. This study estimates the number of people who have participated in the microfinance institutions (MFIs) in India and have crossed the USD 1.25 a day consumption threshold. The time period considered for our study is 1990-2010.

To arrive at the results we make a crucial distinction between MFIs that have either different organizational setup or follow different lending models. In other words, apart from the NGO-BLP (Bank Lending Programme) combination, the MFIs are classified into 9 cells. Each cell is a combination of a loan type (joint liability, individual liability or self-help group) with any one of the three organizational types (NGO, NBFC, others). There were 27 MFIs who participated in the study. The total clients surveyed from these MFIs were more than 15,000. However, after "cleaning" the data, we could use the data for only 14746 clients. Apart from this we sampled 822 households who are MFI clients through the SHG Bank Linkage model.

To arrive at the all India level estimate, we first divide the country into 5 distinct regions (North, South, East, West-Central and North East). We then identified the top 14 states whose MFI clientele is at least 1% or more of the all India total. These 14 states together have approximately 95% of the total MFI clientele in India. Thus the states are fairly representative of all the MFI clientele in India.

MFIs in India are not homogenous. Significant differences exist across MFIs either because they have different organizational structure or they practise different lending models. Therefore, the MFIs are classified into 9 cells. Each cell is a combination of a loan type (joint liability, individual liability or self help group) with any one of the three organizational types (NGO, NBFC, others). For each of the states, MFIs were identified belonging to each cell. There were 18 cells considered for each State-9 in rural and 9 in urban. There were 27 MFIs and 6 SHG Bank linked NGOs who participated in the study. The two most populous cells are NGO-SHG and NBFC-JLG combination.

From the client list provided by the MFIs, households were selected randomly (simple random sampling without replacement) for survey. We surveyed over 15,205 households. However, after omitting those observations where the specific asset values were missing , we were left with 14746 households. The household questionnaire captured the current asset distribution as well as the asset distribution at the time of their joining the specific MFI. Recall method was used to assess the latter.

The estimates were obtained from the collected data by comparing the asset scores of both the recall and current asset distribution. Different scorecards for rural and urban households were developed for each of the 14 States. This process ensures that, once we have the scores of a set of people, we can, with some pre-determined error, say whether they are below or above the consumption threshold. The consumption threshold was arrived at by using the purchasing power parity (PPP) measure of USD 1.25. Although the ideal scenario would have been one where an exact consumption expenditure survey was done for the households for the period when they were not MFI clients. This was not possible now given that recall of consumption expenditure of a distant past is difficult. Therefore, a scorecard that is based on asset status is the most appropriate technique for the current study.
Our key results are summarized below:

- At an all India level, (approximately) a net of 12% (9 million) of all MFI clients (74 million) have crossed the USD 1.25 a day consumption threshold from below.
- At an all India level, (approximately) one third of all MFI clients who started as 'poor' (below the USD 1.25 a day consumption threshold) have crossed the USD 1.25 a day consumption threshold from below. At an all India level, a net of 12% percent of all NGO clients crossed the threshold from below.
- At an all India level, a net of 12% percent of all NBFC clients crossed the threshold from below.
- At an all India level, a net of 12% percent of all NGO –SHG clients crossed the threshold from below.
- At an all India level, a net of 10% percent of all NBFC-JLG clients crossed the threshold from below.
- At an all India level, a net of 12% percent of all SHG Bank linkaged clients crossed the threshold from below.

1.2 Limitations of the current study and some caveats

For a study of this scale, the shortcomings are often unavoidable. These often arises owing to geographical spread, long time horizon etc. [2] These are mostly operational. However, there are other shortcomings the current study has owing to complexities involved in the research design process. It is worthwhile to mention some of the shortcomings of this study.

Self selection (Selection of MFIs): While more than 200 MFIs were approached to be part of the study, only 37 MFIs agreed and we could use the data of only 27 of them. It is difficult to fathom the exact reasons why some MFIs chose to be part of the study while others did not. One reason most commonly put across by the non participating MFIs was that the data of the

[2] Indeed, post November 2010, we could conduct no surveys in Andhra Pradesh owing to recent troubles with MFIs in that region.

clients were not readily available in a digitized form. While this could certainly be true, it is entirely possible that these MFIs (or more importantly their clients) were different from the ones we studied. However, even though certain MFIs were initially reluctant to be part of the study, we could convince them to be part of the study later on. This took care, up to an extent of the self selection problem where all those MFIs who opted out were different from those who did not.

Recall survey: Our methodology involved the clients recalling their economic status (by the assets they possessed) before joining the particular MFI. Recall survey can have error especially if the recall period is long. This could particularly influence our estimate of poverty status of the clients before they became MFI clients.

Client drop outs: We could not survey clients who were earlier with the MFI but are now no longer there. This meant we lost out vital information about those clients who either, had crossed the threshold and no longer needed the MFI or who have now become un credit worthy for the MFI. In either case, this is valuable information that is missing that could affect the final estimates. This study is implicitly assuming that the distribution of clients in the sample in terms of client age, net of client drop out represents the population distribution. Therefore, this means that our results are based on the current client list and not the entire clients who has ever been a MFI client.

Multiple MFI clients: It is entirely possible that a household who is a client of one MFI is also the client in another. There are reasons to believe that these clients are different from those who are associated with a single MFI. This is because, often clients find themselves in debt trap—borrowing from one MFI to pay off the other. These clients are definitely in a worse economic scenario compared to others.

Exogenous shocks: Most MFI clients, who come from poor areas often receive exogenous shocks that can affect the poverty status largely. For example, the Sunderbans area of South 24 Parganas district was affected by cyclone Aila in May 2009 which caused tremendous economic damage. Therefore, almost the entire client base in that area (irrespective of the lending model or organizational type) are currently worse off than where they were when they joined. While some shocks like the above are observe and can be adjusted for, most shocks are unobservable. Further, in 2010, large part of India where we carried our survey was inundated by flood.[3] This could have an immediate impact on current poverty status.

Technical model: The score card is parsimonious and based on only maximum possible 12 items. Many of the possible items that can explain poverty status better are left out because these items may not constitute easy recall. Therefore, although it is difficult to ascertain the nature of bias, working with few assets may under or over report poverty status than the case had we used more items.

Unrest among MFI clients in Andhra Pradesh: Around October 2010, an unrest among MFI clients in Andhra Pradesh prevented us from carrying any further survey there after

[3] Assam, Bihar and parts of Northern India had seen enormous flood in July 2010.

November 2010. Andhra Pradesh has largest number of MFI clients (approximately 1/3rd of all clients pan India). Although our sample has approximately 39% of the clients from Andhra Pradesh, our round 2 surveys that were aimed at validation as well as surveying SHG bank linkage clients could not eventually take place.

Chapter 2: Methodology

The research methodology to arrive at the final estimates involved the following four steps. First, we drew up the estimation process by designing the appropriate sampling framework. Second, based on the framework, the actual survey was conducted. Third, scorecards were developed that could classify households into distinct categories. The final step involved arriving at the population estimate after the sample estimates are arrived at. In this chapter, we will describe the estimation process and the survey conducted. We will describe the scorecard in chapter 3. In chapter 4, we will provide the main analysis and population estimates.

2.1 Setting up the estimation

The estimation process involved household survey. This is because; our objective was to identify the households that became MFI clients when they were among the poorest (i.e. with per capita consumption below USD 1.25 a day). Among those households, we would then identify those households who are no longer below the USD 1.25 a day consumption threshold. There are two groups of households who can satisfy this criterion --- those who are clients now and, those who once were, but are currently not. In our study we only consider the first group as information about the second group is unavailable.

2.1.1 Geographical distribution

Since we were not trying to establish any pattern regarding the behaviour of MFIs and households that relate to them, the regional division was driven purely by considerations of operational ease. That is, we are not interested in providing estimates separately for each region. This is because, it is entirely possible that there are types of MFI activities that are present in one region but is entirely absent in the other. However, as we are only interested in the all India level estimates, irrespective of whether such MFI activities are absent from one region or the other, it will get reflected in the all India level estimates. The main criterion for such division was that we have data at the level of the regions. Since we aggregated the states into regions, as long as we have all necessary data at the state levels, we can aggregate them to obtain first region wise estimates and then India wise estimates.

Following are statistics from the Bharat Micro-Finance Report 2009 published by Sa-dhan: As on March 2009, there are 425 registered MFIs in India catering to 16.45 million clients covering 413 districts. We divided up the country into 5 regions: North (Punjab, Himachal Pradesh, Uttarakhand, Uttar Pradesh, Rajasthan, Haryana, Delhi); East (Jharkhand, Bihar, West Bengal, Orissa); North-East (Tripura, Nagaland, Manipur, Assam, Sikkim);

Central+West (Chhattisgarh, Madhya Pradesh, Gujarat, Maharashtra, Goa); and South (Andhra Pradesh, Karnataka, Kerala, Tamilnadu, Pudicherry, Andaman and Nicobar Islands).

Table 2.1 outlines details about these 5 regions. Once the regions were decided, we move to the next stage, the selection of the states.

2.1.2 Selection of States

We restricted ourselves to states within each region so that they covered at least 1 per cent of all clients. This gave us a total of 14 states: 2 in the North, 4 in the East, 1 in the North-East and 3 in the West+Central and 4 in the South.

From Srinivasan (2009), it is evident that the following 14 states (Andhra Pradesh, Tamil Nadu, West Bengal, Orissa, Bihar, Jharkhand, Karnataka, Maharsthra, Madhya Pradesh, Rajasthan, Kerala, Chattisgarh and Assam) constitute 95% of all MFI clients (MFI clients as well as SHG BLPs).

Once the states were identified, we move to the next step, that is identifying the MFIs.

2.1.3 Selection of MFIs

MFIs are different in their organizational structure. In general, we divide them into profit and non-profit organizations, those directly connected to banks and those to the government. Table 2.3 outlines the different organizational structures followed by the MFIs. In table 2.3, Society, Trust, Cooperative and Section 25 Companies are categorized as group 1. The Non Banking Finance Companies form group 2 while the Mutually Aided Cooperative Society (MACs) and Local Area Banks (LABs) are put together as having a similar organizational structure as group 3.

There is one other categorization of MFIs that is important --- their activity type. MFIs can operate through joint liability lending (JL), self help groups (SHG) or, through individual lending (IL). Any member in any region can, therefore, be in one of 9 potential cells, each made up of a loan type (joint liability, individual liability, or through a self help group) with any one of three organizational type of MFI (NGO, NBFC, others).

There is another type of cell that is predominant in India, which we list separately. This is the SHG-Bank linkage programme (BLP). In fact, this is the cell that has the highest number of clients. The SHG—Bank Linkage Programme was launched by NABARD in 1992 for linking 500 SHGs with banks as a pilot project. Currently there are more than 59 million clients(see Srinivasan 2010). The reason we differentiate the BLPs from the cell NGO-SHG is because, unlike the NGOs in the cell NGO-SHG, these NGOs act as financial intermediary between the banks and the SHGs by accepting contractual responsibility for repayment of the loan to the bank. They do not directly lend to the SHGs.

2.2 Household characteristics: entire sample

Some key statistics of the households in the sample are discussed below.

In table 2.8 we present the household distribution according to the clients' year of joining. In our sample, 90% of the clients have joined on or after 2002. This skewedness itself has implications for the study. This is because, our failure to capture too many clients who had longer (greater than 10 years of association with the MFI) loses out on a vital information: why do MFI clients quit? The reasons could be (a) purely random (b) they get better opportunities and hence do not need the MFI anymore or (c) they have become unbankable for the MFI. It is the last two possibilities that would affect our final estimates. However, without any information on the clients who have quit now, we can at best assume that the three factors cancel each out in an overall sense and hence the final estimates we obtain are unbiased.[4]

In table 2.9, we present the household size, number of dependents and the education level of the household head. The frequency plots for the same are given in figures 4.1-4.3. Note that the modal household size is 4. For both rural as well as urban households, 4 member households form the highest percentage (almost one third). From the figures it is evident that the household size is also single peaked at 4. The number of dependents for both rural and urban household is highest at 2 and 3. That is most (together close to 60%) of the households have between 2-3 dependents (those with a age below 18 years). The literacy status of the household head has stark differences across rural and urban households. While close to 30% of the rural households are headed by individuals who are not literate, the figure is almost half for the urban households. On the other hand, while a little over 20% of the rural household head has completed school education (secondary), the corresponding number is twice for urban households. This is a stark difference between the two types of households.

In table 2.10 we present the nature of assets possessed by households both before joining the MFI as well as now. The determination of movement, reverse movement as well as net movement in our model is eventually determined by these assets through the scorecard.[5] This table requires careful interpretation. It is evident that expensive consumer durables like AC, fridge, Car, PC are still possessed by less than 90% of the households in our sample. For all India as well as for rural and urban areas, the improvement (difference in terms of percentage of households who had them earlier and who have them now) is marginal. The column "Impr" is simply the difference between percentage of households who possess the asset now vis a vis the percentage of households who had them earlier. We identify all those assets where the improvement is significant (that is at least 10% or more households have these assets now compared to the scenario when they joined the MFI). Among all those assets that

[4] Later, when we analyze movements, we will discuss the emerging pattern of poverty among older clients and newer clients.

[5] However, not all the assets presented in 4.19 were found to be significant for all the States or the sectors.

has shown significantly increased possession, if less than half the households had the asset before joining the MFI, we identify such assets. These assets are boldfaced. We present some interesting facts below.

Possession of mobile phones shows the most remarkable progress. From an all India level of 35% of households who had mobile phones when they joined, the number now stands at 81%. In fact it features among the top three assets possessed by all households. This is encouraging as almost the entire population of MFI client seems to be connected. Note that most assets which show significant improvement do not carry huge positive weights in the scorecards. Indeed some of the assets are more likely to be owned by poorer households than non poor households (sewing machines, radio, tape recorders).[6] However, it is important that we consider all possible reasons as to why certain households may own an asset while some others do not.

While possession of most assets in the list is demand driven, three particular items have often supply constraints that prohibit households from possessing them. These assets are- having bank accounts, having electricity and possessing LPG. Opening of bank accounts depend upon access to banks, access to electricity (especially in rural areas) depend upon the electrification program for the area and a LPG connection requires a nearby supply unit along with residential requirements. We find some encouraging movement regarding bank accounts. We find, from less than one third of the MFI clientele who had bank accounts before they joined the MFI, more than half the population now has a bank account. This is encouraging but still more needs to be done as almost half the MFI clientele (that is close to 40 million households) is financially excluded. Of all the MFI clients, we find the movement regarding electricity has been uniform. From 73% of households who earlier had electricity, close to 90% of the households have it now. LPG on the other hand has been the least encouraging. The movement has been minimal (around 7% all India and 5% in rural parts) and still more than 50% households do not have LPG connection.

In a nutshell, the asset distribution from table 2.10 suggests that (1) certain supply bottlenecks are reducing over time (2) policy directions that is built on mobile phone penetration is more likely to reach the population more efficiently (3) there are not significant movements in terms of assets possessed that 'matters' to infer a household that has crossed the threshold.

[6] The asset ownership data across various Socio Economic Categories of gives us certain assets like electrical iron, sewing machines in rural and bicycle, cookers in urban areas is more likely to be owned by those who are economically worse off.

Chapter 3: Scorecards and Multipliers

In this chapter we explain two important instruments that will be used to arrive at the aggregate estimates. The first one is the scorecard. This is the instrument that will determine the sample estimates. The scorecards are used to calculate the net movement of the continuing clients between the point when they entered the MFI and the point at which the survey was conducted. The questionnaire is also designed keeping in mind the scorecard requirements. The second important instrument is the multiplier. The multipliers are necessary to convert sample estimates into population estimates. In section 3.1 we present the scorecard and in 3.2 we present the multiplier (the technical details of both are relegated to appendix F).

3.1 Scorecards

3.1.1 Why scorecards

As we were interested in counting the number of households who had moved up from below USD 1.25 consumption per capita per day to above it, our methodology required a 'recall' of consumption status (of the period when they were not MFI clients) as well as an assessment of the current consumption status. The ideal scenario would have been one where we find out the current household consumption expenditure and the household consumption expenditure of the period when they were not MFI clients. However, since the year when they became a MFI client for the first time can be in the distant past, recall of consumption expenditure would be impossible. Therefore, the next best strategy is to create a scorecard that can be used to proxy the consumption thresholds. Thus, we use a scorecard approach to assess these two status points. A scorecard is a simple tool that specifies scores which households can be given based on the possession of certain assets and conditions. The scorecard also classifies the population into one of the many scoring bins each calibrated to a separate likelihood of being below the USD 1.25 consumption threshold. Once, the likelihoods are established, we would know approximately how many individuals in a particular bin are likely to be below the threshold. The sum of all such individuals across different bins will give us the total estimate of poor people in the population.

3.1.2 Our Scorecards

We developed scorecards based on two large rounds of NSS (round 55 and round 61). Both rounds were based on consumption expenditure survey. While Round 55 was conducted in 1999-2000, round 61 was conducted in 2004-05. From round 55, we created one national (all India level score card) and from round 61, we created have 10 different state sector score cards and one national level score card. All the 11 scorecards (based on round 61) are in table 3.1 while the score card based on round 55 is in table 3.1a. The current report is based on round 61 scorecards only.[7]

To create the scorecards, we ran logistic regressions. We then collected the coefficients from the regressions to form the weights for the scorecards. We transform the logit coefficients into scores for each assets by a simple transformation (e^{β_i}) to each of the coefficients β_i, then scaling the scores such that the maximum score a household can get in our scorecard is 100 while the minimum score is zero. Typically a higher score would indicate that the household is less likely to be poor (that is below the pre defined consumption threshold). We partitioned our scorecards to 5 equal sized bins. We ensured for the scorecard chosen, the poverty likelihood percentages in each of the bins must be "well behaved". That is, we should typically expect the poverty likelihood to be highest in the first bin (score range: 0-20) and gradually reduce as we move up (say 20-40, 40-60 etc). The highest number of bins we could obtain keeping both the criteria were 5 bins. From our analysis on the 'training sample', we find these bins have different likelihood of collecting 'poor' people. For example, our score card for Andhra Pradesh (rural) reveals that the likelihood of a person being below the consumption threshold is 55% if the person gets a score between 0-20, it reduces to 31% if the person gets a score between 20-40, 6% if the score is between 40-60, 4% if it is between 60-80 and 1% between 80-100. After performing this exercise, we were left with 11 scorecards as mentioned above.

Prediction of actual poverty figures from the NSS 61 and NSS 62 rounds are given in table 3.4. Our score card could be applied without any adjustments in only three state sectors (AP1, AS1 and TN1). This is because, in NSS round 62, AC and cooler are clubbed together while our score card treats them separately. The specific state sector scorecard we have for these three state sectors do not assign any positive weight to either AC or cooler. From the table it is evident that the bias is mostly one directional. That is, if the predicted bias is positive (under predicting poverty rate) in round 61, the same is true for round 62. This implies, while the current as well as the earlier poverty status of the MFI clients may be under or over predicted. However, it is difficult to ascertain whether the net movement will be affected (and if so, in which direction). Therefore, there is a case of overestimating poverty rates especially in the urban areas of Andhra Pradesh, Tamil Nadu, Uttar Pradesh and West Bengal.

[7] However, the estimates of movements based on round 55 (for clients who joined before 2004 are separately mentioned in chapter 4. The net movement estimates across the two score cards are similar). The reasons for using the scorecard based on round 61 only are two. One, a debate exists regarding reconciliation of poverty estimates obtained from round 55 with other NSSO rounds (Sen and Himanshu, 2004, Deaton 2004) as a different recall period was employed for this round. Two, post 2000, Bihar was broken into Bihar and Jharkhand, Madhya Pradesh into Madhya Pradesh and Chattisgarh while Uttar Pradesh into Uttar Pradesh and Uttarakhand. Since our current sample has Bihar, Jharkhand, Madhya Pradesh, Chattisgarh and Uttar Pradesh, we chose to go with scorecards obtained from round 61 (where all these states appear separately).

3.2 Calculating the Multipliers

Through our survey, we get sample estimates for each cell in a region. In order to get to the all India level population estimate, we have to weigh it with the appropriate multipliers. In other words, for each cell in a region, we will have to calculate the total number of MFI clients. Unfortunately, till date, there is no data base available that gives us the population figure for each cell in a region.[8] The existing data bases have information about (a) total client base of MFIs (b) the states in which they operate (c) their rural and urban break up of clients and (d) the types of lending practices they adopt. However, the data is available only at the aggregate level which makes it impossible to break up the clients into the 18 cells. This is because, often MFIs operate in more than one States and follow more than one type of lending. Thus, we cannot break up the client base of those MFIs either state wise or lending category wise. Therefore, we had to estimate the population numbers for each cell. We used the following approximation technique to arrive at the population figures. First, information on all the factors (a)-(d) was available with us for all the 27 participating MFIs. From the details available for the 27 participating MFIs, we populate the cells where they are functional. We used their 2009 client list to make it comparable with other data bases. We take the all India population base (as of 2009) from the data base maintained by Sa-dhan and Srinivasan (2009). This data base had the following relevant details: Names of the MFIs, rural and urban clients, their organizational structure, types of lending followed as well as the States in which they operated. This data base has details about 234 MFIs. From this data base, details of the 27 MFIs whose data has already been used, is left out as the information about their clients are already incorporated

Next using the interstate proportions (as in table 2.2), the clients of the remaining MFIs are distributed. Once we have estimated the clients per state, we use the rural urban ratio of the MFI to distribute the clients within each State where they operate. We found out that there were 26 MFIs reporting more than one type of lending (Srinivasan, 2009). Since we do not have any aggregate estimate of MFI clients according to the lending model, we decided to omit these 26 MFIs. These 26 MFIs constitute a negligible (2%) of all MFI clients in India. Therefore, our MFI client base, used for population estimate covers 98% of the total MFI clientele. Once the population of clients of a MFI for a given lending type is determined for a state, we proportionately distribute the clients into rural and urban areas. This proportion is arrived from the proportion of rural and urban clients reported by the MFI in the data base maintained by Sa-dhan. The All India level cell wise aggregates are given in tables 3.5-3.7.

From tables 3.5 -3.7, it is evident that MFIs that are NGOs or are NBFCs togather have more than 90% of the total clientele. The other seven forms of MFI lending combinations have negligible client base. Note that, once we obtain the individual estimates for each of the cells, we can use the population figures for the cells to estimate the total number of households who have moved from below the USD 1.25 a day consumption threshold. However, as our

[8] It is worth recalling that a cell in a region consists of a MFI organizational type combined with the lending model it follows. Further the cell is defined over a state and the appropriate sector-rural or urban.

aggregation method will separately involve estimation for rural and urban clients, we present the population grids for rural and urban separately.

Note that the rural clients form 80% of the total MFI clientele. Consistent with the all India levels, the cells NGO-SHG and NBFC-JLG make up almost 88% of the total client base. The client distribution cell wise for urban areas is given in tables 3.7.

Urban clients, who make up only 20% of the total clientele, also exhibit similar pattern to the ones seen across India and rural sector. The two cells NGO-SHG and NBFC-JLG again constitute approximately 88% of the total urban clientele.

Chapter 4: Main Results and Conclusion

4.1 Main Results

The main findings are given in this chapter. In section 4.1, we present the main results while section 4.2 concludes.

Our sample covered 14 States and 63 districts. The state and district wise sample spread by sector is given in table 4.1. Note that Andhra Pradesh followed by Tamil Nadu and West Bengal forms majority of our sample. Further, 64% of our sample comes from rural sector. In tables 3.9, we present the cell wise sample size by cells.
To calculate the number of households who crossed the threshold, we estimated the number of households who were below the threshold when they joined the MFI and then estimated the number of households who are above the threshold now. The difference in count between the two groups of household gives us the net movement of households from below the threshold to above it.

Our aggregation unit is by cells. That is, we aggregate according to the 9 cells. For each cell, we calculate the rural as well as urban movements (per state present in that cell) and then aggregate them upwards to obtain the all India aggregate.

The steps we follow to arrive at the final figure is explained below.[9]

Consider the cell G3-IL. At an all India level, there are 41,033 entries for this. The cell size is distributed among these four state sectors-Andhra Pradesh (urban and rural) and Karnataka (urban and rural). The respective population numbers are: 29733, 3113, 3360 and 4827. For these four state sectors, we use the Andhra Pradesh (rural) score card to score the Andhra Pradesh rural clients and the all India score card to score the other three sector clients. In table 3.2 we present the observed likelihood ratios (using the appropriate scorecard) for each of these 4 state sectors.

Consider Andhra Pradesh rural (for the calculations, refer to table 4.1). Our sample had 866 observations. After applying the scores to the scorecard, we find that the current poverty status (mapped into the respective bins) of the MFI clients are as follows: 35 of them are in bin 1, 390 in bin 2, 299 in bin 3, 116 in bin 4 and 26 in bin 5. When multiplied by their respective likelihood of being poor, we have 19, 120, 17, 5 and 0 number of poors from each bins respectively. This means, in our sample, there are 162 (19+120+17+5)[10] households below the threshold. Therefore, the percentage of poor clients in our sample is 19% (162/866*100). Identical calculations to assess the poverty status of clients before they joined reveal that 33% (288 out of 866) clients were below the poverty status. We now multiply

[9] We are presenting the explicit calculations for only one cell for simplicity. The calculations for all the other cells follow the identical exercise.
[10] The column sum adds to 161 owing to rounding off error, the actual calculations reveal 162.

both the percentage figures by 29733 (the population weight for this cell). This gives us 5561 clients are below the consumption threshold now while and 9914 clients were below the consumption threshold earlier. We repeat the same exercise for the other three state sectors. For each of the other three state sectors we use the all India score card and use the respective likelihoods. The eventual number of rural clients who are currently below the threshold is 6988 (5561 from AP rural + 721 from AP urban + 515 from Karnataka rural and 191 from Karnataka urban). The corresponding figure for poverty status of the clients before they joined the MFI is 12708 (9914 from AP rural + 689 from AP urban + 735 from Karnataka rural and 1371 from Karnataka urban). The current percentage of clients who are poor is 17% (6988 out of 41033) while the percentage of clients who were poor before they joined was 31% (12708 out of 41033) . These are the percentages reported in the cell G3-IL in tables 4.2-4.4

Applying the calculations similar to above for all the state cells across the state sectors and aggregating it at the all India level gives us "***at an all India level, a (net) 12 % of all MFI clients have crossed the USD 1.25 a day consumption threshold from below since their joining post 1990***"[11]

The above estimates must be seen with the following key observations;

- Approximately 37% of the clients were poor when they joined a MFI
- Approximately 40% of the rural clients were poor when they joined a MFI

The above two points highlight the fact that the MFI clients have usually been poor (40% below the USD 1.25 a day consumption threshold) and that a significant portion of them (approximately 1/3rd) have crossed the threshold from below.[12]

Through tables 4.2-4.3 we find the client movements across different MFI cells. We find that NGOs as organizations and SHG as a lending method have seen 12% movement. The NGO-SHG combination, which attracts highest number of clients (exceeding 56 million) has 12% net movement and also has highest percentage of poor clients (41%). Therefore, one can say the NGOs , the SHG lending mode and most importantly the NGO-SHG combination does attract the poor. We find that almost 41 % of the SHG clients were below the threshold when they joined. The percentage of clients who were below the threshold among SHG –BLP clients stand at 40% while their (net) movement is 12%. The other popular model, NBFC-JLG shows a movement of 10%. However, the NBFC –JLG model seems to attract the better off (only 32% of the clients were poor before they joined). It appears that the LAB and MACs has the best record in terms of movements for organizational type. However, as these are limited to a specific geography (mostly Andhra Pradesh and Karnataka) it is difficult to generalize all India level inferences from them.

[11] Depending upon the rounding off error, the number may vary between 11-12%.

[12] If we were to use the scorecard based on round 55 to score all clients who joined before 2004, the (net) movement would be 10% (35% poor when they joined versus 25% poor now) and if all clients who joined before 2000 were scored using the same score card (note 5 states UP, Bihar, MP, Jharkhand and Chattisgarh were different from pre and post 2000), the (net) movement would be 11% (36% poor when they joined versus 25% poor now).

As we compare rural and urban movements (tables 4.4-4.7), two interesting facts emerge. One, the net movement figures do not change much (12% rural versus 11% urban). Two, what changes is the percentage of poor people these MFIs serve in these two sectors. While 40% of the rural clients (while joining the MFI) were poor, the same number is 25% for urban clients. Finally we see that the NBFC-JLG cell does better in rural area than in urban area.

We now take up the movements at the state level. The state wise movements (as the difference between percentage of clients who were below the consumption threshold when they joined and percentage of clients who have crossed the threshold now) are given in table 4.8. There was 39% poverty rate among the clients when they joined which now stands at 27%. It appears that a random cross section of MFI clients would pick up more of the poor households than a random selection from the population at large. From table 4.8 it is evident that the southern states have shown higher movements than the rest. Coupled with the fact that the rural movements are higher than the urban, a pattern emerges whereby success of MFI penetration is driven by the extent to which it manages to push clients from below to above the threshold. From table 4.9 we get a much more disaggregated movement in terms of districts. We find that there are some districts which have registered negative movements.

How does the movement change with years of association? Table 4.10 and the figures 4.4-4.6 capture this.

Let us consider table 4.10. The second column gives us the current poverty status while the third column gives us the poverty status of the clients when they joined this particular MFI. The column labelled movement (column 4) is the difference between column 3 and column 2, while the column labelled percentage movement (column 5) is the entries corresponding to column labelled movement divided by column 3. In other words, column 5 corresponds to net percentage movements as a percentage of poor clients by their years of joining. The last column is the estimated poverty status of households in India.[13] Note that, the reliable estimates come from the large rounds (that is rounds 55, 60 and 61 corresponding to years 1995, 2000 and 2005 in table 4.10). However, what stands out from table 4.10 is that the MFI clients have been on an average poorer than the all India level. This is to say, on any given year (post 1995), the cross section of MFI clients had more poor households than an all India cross section of population. This is evident from comparing the entries in column 3 and column 6 of 4.10. We plot the same in figure 4.5. Note that, we cannot compare the year on year movements of clients with the corresponding all India figures because our data calculates the change taking 2010 as the reference year. By looking at table 4.10 and figure 4.5 it is evident that the poverty status of MFI clients as well as the all India poverty status is falling over the years. Although it appears that higher percentage off MFI clients seem to

[13] Although there is no reliable year on year poverty estimates available for India, by compiling figures from various studies as well as NSSO rounds we generate the entries corresponding to this column.

graduate out of poverty than average poor households in India, it is important to note that, the net movement of MFI clients cannot be attributed to the MFIs.[14]

Finally, from table 4.10 and figure 4.6, it appears that the movement (column 4) as well as the percentage movement (column 5) seems to peak around 2004 and 2005. This could be indicative of the fact that it may take 5-6 years for a typical poor client to cross the threshold. This could mean (a) that the net movement will be low for clients who joined recently and (b) older clients who still continue with the MFI form a special category who find it more difficult to cross the threshold. However, these results could also be driven by the sample properties. From table 2.8, note that in our sample, only 17% of the clients had joined MFIs before 2004. Further, given that our sample did not have any households who are drop outs, older clients who may have crossed the threshold and are now no longer with the MFI are not there in the study.

The main findings from table 4.10 are (a) MFI clients have been on an average poorer than the all India level and (b) the poverty status of the MFI clients as well as in for India are falling and (c) there could be an optimum threshold of years of association (4-6 years) and net movement of MFI clients.

While it is impossible to identify households who have moved, one can employ a proxy to capture some of those households who may have possibly moved. This can be done by picking up all those households whose score were below 20 when they joined (implying a likelihood of being poor exceeding 50% in all the cases) and counting them as 'moved' if their current score exceeds 60 (likelihood of being poor around 10% or less in most cases).[15] It is not that all households who are identified as such have surely moved, but in an expected sense, these households are most likely to have moved. In our sample, we find such households form 15% of our total sample. It is natural to ask: what are the some of the prominent characteristics of such households? In fact, we ask a more direct question, what household characteristics can be more prominently associated with movements.

In table 4.11 we present some of the household characteristics that are more prominently associated with movements. The bold faced items are the ones which show higher chances of movements. For example, at an all India level, 23% of the salaried households are likely to move. The prominent characteristics that may lead to higher movements (all India level) are regular salary earning, possessing bank account, pucca house. When we look at the household types, we do not find any prominent characteristics for the rural sector whereas being a salaried worker or possessing pucca houses are associated with higher movements in urban areas.

Finally, how different are the results from our round 1 surveys and the round 2 surveys where we carried a validation exercise for those MFIs who had mostly provided their own enumerators. The movements (sample estimates only) were 11% in round 1 and 9% in round

[14] The role of MFIs can only be ascertained after we carry out an impact study.

[15] Effectively we are associating movement with those households who had started in the lowest bin and moved atleast 2 bins upwards.

2. In table 4.12 the individual sector wise movements for each of those 10 MFIs are given. Therefore, at an aggregate level the difference in movements is not enormous.[16]

4.2 Conclusion

We find that at an all India level, a net of 12% of all MFI have crossed the USD 1.25 a day consumption threshold from below. The estimates are obtained after surveying over 15,000 households of over 27 MFIs and various SHG Bank linkage programmes. The study spanned across 14 states and 63 districts all over India. We find that certain types of MFI organizations and lending types perform better. The difference in terms of various geographical regions is significantly different while there are no prominent household characteristics that explain these movements. We further find that for a typically poor client, it would take between 5-6 years of MFI association to cross the USD 1.25 a day consumption threshold. The study estimates the number of poor who have benefitted from being associated with the MFI, but it does not imply any causality for the same.

[16] Most of the MFIs for which the validation survey was done came from the NBFC-JLG cell. This means, if we were to "discard" the round 1 data for which the movements were significantly higher than round 2 movements, the all India level estimates will not change substantially (MFIs 4, 5, 6 (rural only) and 7 could be excluded).

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Appendix A: Tables

Table 2.1: Regional Distribution of Clients

Regions	No. of SHG members	No. of MFI clients	Total Microfinance clients	Clients (%)
Northern Region	2144857	350159	2495016	3
Nort East	1519336	251484	1770820	2
East	11601356	4412391	16013747	22
Central	4768350	1825985	6594515	9
West	4602234	2322505	6924739	9
South	29702998	10863844	40566842	55
Grand Total	54339311	20026368	74365679	100

Table 2.2: State Wise Distribution

State/Region	No. of SHG members	No. of MFI clients	Total Microfinance clients	Clients (%)
Rajasthan	1272921	242926	1515847	2
Northern region	**2144857**	**350159**	**2495016**	3
Assam	1155934	163005	1318939	2
North East region	**1519336**	**251484**	**1770820**	2
Orissa	4091230	1462450	5553680	7
Bihar	1085422	400223	1485645	2
Jharkhand	530712	183321	714033	1
West Bengal	5893992	2366397	8260389	11
Eastern region	**11601356**	**4412391**	**16013747**	22
Madhya Pradesh	1068483	551235	1619718	2
Chhattisgarh	855751	397757	1253508	2
Uttar Pradesh	1392378	812702	2205080	3
Central region	**4768350**	**1825985**	**6594515**	9
Maharashtra	4077255	2208784	6286039	8
Western region	**4602234**	**2322505**	**6924739**	9
Andhra Pradesh	15819427	4949393	20768820	28
Karnataka	4096950	3229378	7326328	10
Kerala	2282969	310646	2593615	3
Tamil Nadu	7460063	2348452	9808515	13
Southern region	**29702998**	**10863844**	**40566842**	55
Grand Total	**54339311**	**20026368**	**74365679**	95

*The 14 states we consider accounts for 95% of all clients (MFI + SHG BLP) in India

Table 2.3: Organizational Structures

Form	Number	Percentage
Society	104	18.80
Trust	31	6.80
Cooperative	8	0.10
MACS	10	0.30
Section 25 Company	22	11.60
NBFC	25	59.70
LAB or any other	16	2.70
Total	216	100.00

Table 2.5: Participating MFIs According to Lending Category

	Individual Lending	Joint Lending/Group Lending	SHG
Group 1 (non-profit Societies, Trusts and Section 25 Companies)	VSSU, Sahara	LBT, GBK, VSSU, Cashpor, Ashajyoti, SMSS, Grameen Sahara	RASS, , PSS, Sahara Manch, Yukti, PMD, VGBK, SNF,Iswar, Prayas, Progress
Group 2 (NBFC)	Satin Care,	VFSPL, SKS, , GVMFL, GFSL, ESAF,Bandhan, Aarohan, BWDA, MGSCS, VAMA, ESAF, GFSL, GVML, Navchetna	Sarvodaya
Group 3 (Rest)	KBSLAB	KBSLAB	Indur, PWMACS

Table 2.6: Participating MFIs and their clients (as on 2010)

MFIs	Total Clients	Type of lending	Organization type	States in which they operate	Sample Size
Adhikar	54189	JLG	NBFC	OR	351
AROHAN	86,327	JLG	NBFC	WB	633
Ashajyothi	1,712	JLG	Society	AP	394
Bandhan	14,54,834	JLG	NBFC	AS,BI, , JH, MA, Meg, OR, Tr, UP, WB	321
BWDA	2,63,968	JLG	NBFC	TN	441
Cashpor	3,19,859	JLG	Section 25	BI, UP	385
ESAF	1,45,701	SHG	Society	CH, KE, MA, MP, TN	608
GBK	17,628	JLG	Society	WB	339
GVMFL	3,62,624	JLG	NBFC	Pon, TN	962
GFSL	2,56,301	JLG	NBFC	WB, KA	143
Grameen Sahara	4,200	JLG	Society	AS	77
Indur Intideepam	44,110	SHG	MACS	AP	653
KBSLAB	1,85,495	IL, JLG	LAB	AP, KA	2,271
LBT	2,760	JLG	Trust	MP	91
MGSCS	16,642	JLG	NBFC	AP, TN	489
Navachetana	2,609	SHG	Society	KA	100
PSS	42,075	SHG	Society	AP	397
RASS	51,528	SHG	Society	TN	775
Sahara	69,736	IL	Society	WB	185
Sarvodaya	5,80,388	SHG	NBFC	BI, JH, MP, RA, TN	613
Satin	56,863	IL	NBFC	Cha, Del, Har, Pun, RA, UP, Utt	42
SKS	39,53,324	JLG	NBFC	AP, BI, Cha, Del, Guj, Har, HP, JH, KA, KE, MP, MA, OR, Pun, RA, UP, Utt, WB	1,210
SMSS	36,070	JLG	Society	AP	618
VAMA	3,286	JLG	NBFC	MP	180
VFSL	77,206	JLG	NBFC	WB	188
VSSU	17,051	IL, JLG	Society	WB	582

Table 2.8: Client joining by years

2009	1,111	7.53	7.53
2008	2,031	13.77	21.31
2007	2,572	17.44	38.75
2006	2,854	19.35	58.1
2005	2,699	18.3	76.41
2004	1,000	6.78	83.19
2003	678	4.6	87.79
2002	557	3.78	91.56
2001	530	3.59	95.16
2000	373	2.53	97.69
1999	130	0.88	98.57
1998	71	0.48	99.05
1997	72	0.49	99.54
1996	7	0.05	99.59
1995	34	0.23	99.82
1994	13	0.09	99.91
1993	8	0.05	99.96
1992	5	0.03	99.99
1991	1	0.01	100

Table 2.9: Household Characteristics

	Rural Percentages	**Urban** Percentages
Number of Dependents		
None	4.9	0.0
1	26.6	28.3
2	28.4	31.6
3	30.2	31.1
4	8.1	7.5
5	1.7	1.4
6	0.0	0.0
Household Size		
1	1.8	1.0
2	8.0	10.0
3	16.6	20.4
4	33.9	34.4
5	22.2	20.6
6	10.4	9.3
7	4.1	2.5
8	1.6	0.9
9	1.0	0.5
More than 10	0.4	0.3
Literacy (Household head)		
Not literate	29.3	16.3
Literate without formal schooling	13.6	11.1
Literate but below primary	7.0	5.7
Primary	11.5	11.1
Middle	15.5	15.6
Secondary	12.8	20.2
Higher secondary	6.6	11.7
Diploma	1.4	3.0
Graduate	2.0	5.1
Post graduate and above	0.4	0.3

Table 2.10: Items in the sample of households (percentages)

	All India	All India	All India	Rural	Rural	Rural	Urban	Urban	Urban
Items	Poss earlier	Poss now	Impr	Poss earlier	Poss now	Impr	Poss earlier	Poss now	Impr
Almirah	40.6	60.7	**20.1**	33.8	54.4	**20.6**	52.6	71.9	19.3
Chair	65.2	80.7	15.5	59.4	75.8	16.4	75.6	89.4	13.8
Suitcase	71.7	79.1	7.4	69.6	75.3	5.7	75.5	86	10.5
Dunlop pillow	17.2	32.6	**15.4**	12.3	25.9	**13.6**	26	44.6	**18.6**
Carpet	57.9	61.1	3.2	55.7	56.7	1	61.7	69.1	7.4
Radio	36.2	36.4	0.2	34.3	33.4	-0.9	39.8	41.8	2
TV	43.5	79	**35.5**	39.6	74	**34.4**	50.5	88	37.5
VCR	9.6	32.8	**23.2**	8.1	28.3	**20.2**	12.4	40.7	28.3
Camera	3.5	8	4.5	2.8	5.8	3	4.9	11.8	6.9
Tape recorder	10.2	21.8	**11.6**	7.9	16.5	**8.6**	14.3	31.2	16.9
Electric Fan	67.1	83.1	16	61.9	79.5	17.6	76.5	89.6	13.1
AC	2.3	3.5	1.2	1.8	2.5	0.7	3.2	5.1	1.9
Cooler	3.7	9.5	5.8	3.2	7.9	4.7	4.5	12.5	8
Lantern	67.6	71.6	4	65.3	67.9	2.6	71.8	78.3	6.5
Sewing machine	13.8	25.6	**11.8**	11.2	21.7	**10.5**	18.7	32.6	13.9
Washing machine	2.9	6.4	3.5	2.1	3.9	1.8	4.4	11	6.6
Cooker	26.4	45.3	**18.9**	21.2	36.4	**15.2**	35.8	61.5	**25.7**
Fridge	6.3	16.7	**10.4**	4.2	10.8	**6.6**	10.1	27.4	**17.3**
Electric Iron	24.7	39.5	**14.8**	19.5	33.8	**14.3**	34.2	49.7	**15.5**
Bicycle	58.6	64.9	6.3	60.5	68.3	7.8	55.2	59	3.8
Motor cycle	14	32.7	**18.7**	11	27.5	**16.5**	19.3	42	**22.7**
Car	3.2	4.9	1.7	2.6	4.2	1.6	4.1	6.3	2.2
Clock	76.6	85	8.4	73.6	81.9	8.3	81.9	90.6	8.7
PC	2.8	3.3	0.5	2.3	2.2	-0.1	3.6	5.3	1.7
Mobile	35.1	81.4	**46.3**	32	78.7	**46.7**	40.7	86.4	**45.7**
Pucca house	47.1	59.1	12	43.4	55	11.6	53.7	66.6	12.9
Bank account	30	54.9	**24.9**	28.5	51.4	**22.9**	32.6	61.3	**28.7**
Jewellery	29.5	38.4	8.9	29.5	35.3	5.8	29.4	44.1	14.7
Electricity	73.3	88	14.7	71.3	85.7	14.4	76.7	92.2	15.5
LPG	37.2	44.4	7.2	27.1	32.2	5.1	55.2	66.4	11.2

*The entries that are bold faced shows significant improvement.

Table 3.1: The scorecards that were used to score the households (based on Round 61, NSSO, 2004-05)

	AP(Ru)	AS(Ru)	MA(Ru)	MP(Ru)	OR(Ru)	OR(Ur)	RA(Ur)	TN(Ru)	TN(Ur)	UP(Ur)	India
Items											
Radio	5	10	5	0	8	5	7	5	5	6	6
TV	8	16	4	9	0	5	6	8	6	0	7
Electric Fan	10	13	5	12	10	0	6	5	4	0	8
AC	0	0	27	5	0	0	9	0	17	25	8
Cooler	0	0	0	0	8	9	0	0	0	10	0
Sewing Machine	6	8	0	5	8	9	7	0	6	0	6
Fridge	27	0	18	18	10	10	24	43	27	18	18
Bicycle	5	15	4	0	6	6	5	0	0	0	4
Motor Cycle	21	0	16	23	12	14	8	25	14	17	13
Car	5	17	0	0	16	0	9	0	0	0	7
LPG	8	13	12	21	14	21	9	14	18	12	17
Electricity	6	8	8	8	9	22	11	0	4	13	5

Ru: Rural; Ur: Urban

Table 3.1a: Scorecard based on Round 55, NSSO, 1999-2000

Almirah	5
Chair	4
Foam Cushion	6
Radio	5
TV	5
VCR	5
Tape Recorder	5
Electric Fan	5
Sewing Machine	5
Washing Machine	8
Cooker	4
Fridge	7
Motor cycle	10
Car	7
Clock	6
LPG	8
Electricity	4

Table 3.2: Likelihood Calibration* for the Scorecards Used

Bootstrapped bias, standard error and 95% bias-corrected confidence intervals of the scorecards used for state-sectors (1=rural, 2=urban)

State-sector	Score Bins	Likelihood	Bias	Std. Err	95% conf. Interval	
AP1	0—20	0.6	0	0	0.5	0.6
AP1	20—40	0.3	0	0	0.3	0.4
AP1	40—60	0.1	-0.1	0.1	0.1	0.3
AP1	60—80	0	0	0.1	0	0.2
AP1	80—100	0	0	0	0	0
AP2	0—20	0.6	0	0	0.4	0.6
AP2	20—40	0.3	0	0	0.2	0.3
AP2	40—60	0.1	0	0	0	0.2
AP2	60—80	0	0	0	0	0
AP2	80—100	0	0	0	0	0
AS1	0—20	0.7	0	0	0.6	0.7
AS1	20—40	0.4	0	0	0.3	0.4
AS1	40—60	0.3	0	0.1	0.1	0.3
AS1	60—80	0.1	0	0	0	0.2
AS1	80—100	0	0	0	0	0
BI1	0—20	0.7	0	0	0.6	0.7
BI1	20—40	0.3	0	0.1	0.1	0.3
BI1	40—60	0.1	0	0.1	-0.1	0.2
BI1	60—80	0	0	0	0	0
BI1	80—100	0	0	0	0	0
BI2	0—20	0.7	-0.1	0	0.6	0.8
BI2	20—40	0.3	0	0.1	0.2	0.5
BI2	40—60	0.1	0.1	0.1	0	0.3
BI2	60—80	0	0	0.1	-0.1	0.2
BI2	80—100	0	0	0	0	0
CH2	0—20	0.7	0	0.1	0.4	0.7
CH2	20—40	0.4	0	0.1	0.3	0.7
CH2	40—60	0.1	0	0.1	0.1	0.4
CH2	60—80	0	0	0.1	0	0.3
CH2	80—100	0	0	0	0	0
CHI	0—20	0.8	-0.1	0	0.8	0.9
CHI	20—40	0.5	0.1	0.1	0.3	0.5
CHI	40—60	0.2	0	0.1	0	0.4

State-sector	Score Bins	Likelihood	Bias	Std. Err	95% conf. Interval	
CHI	60—80	0	0	0	0	0
CHI	80—100	0	0	0	0	0
JH1	0—20	0.6	0.1	0.2	0.3	6
JH1	20—40	0.4	0	0.1	0.1	0.6
JH1	40—60	0.1	0	0.1	0.2	0.6
JH1	60—80	0	0	0.1	0.1	0.6
JH1	80—100	0	0	0	0	0.2
KA1	0—20	0.7	0	0	0.6	0.7
KA1	20—40	0.3	0.1	0.1	0.2	0.4
KA1	40—60	0.1	0.1	0.1	-0.1	0.3
KA1	60—80	0	0	0.1	0	0.2
KA1	80—100	0	0.1	0.1	0	0.3
KA2	0—20	0.5	0	0	0.4	0.5
KA2	20—40	0.2	0	0.1	0.2	0.4
KA2	40—60	0.1	0	0.1	0	0.4
KA2	60—80	0	0	0	0	0
KA2	80—100	0	0	0	0	0
KE2	0—20	0.4	0	0	0.3	0.5
KE2	20—40	0.2	0	0	0.1	0.3
KE2	40—60	0.1	0	0	0	0.2
KE2	60—80	0	0	0	0	0
KE2	80—100	0	0	0	0	0
MA1	0—20	0.6	0	0	0.6	0.7
MA1	20—40	0.3	0	0	0.2	0.3
MA1	40—60	0.1	0	0	0	0.1
MA1	60—80	0	0	0	0	0.1
MA1	80—100	0	0	0	0	0
MP1	0—20	0.8	0	0	0.7	0.9
MP1	20—40	0.5	0	0	0.4	0.6
MP1	40—60	0.2	0	0.1	0.1	0.3
MP1	60—80	0.1	0	0.1	0	0.2
MP1	80—100	0	0	0	0	0
MP2	0—20	0.7	0	0.1	0.5	0.8
MP2	20—40	0.5	0	0.1	0.5	0.8
MP2	40—60	0.2	0	0.1	0	0.2
MP2	60—80	0	0	0.1	0	0.4
MP2	80—100	0	0	0	0	0
OR1	0—20	0.8	0	0	0.8	0.9
OR1	20—40	0.5	0	0	0.4	0.5
OR1	40—60	0.2	-0.1	0.1	0.1	0.4

State-sector	Score Bins	Likelihood	Bias	Std. Err	95% conf. Interval	
OR1	60—80	0.1	0	0.1	0	0.3
OR1	80—100	0	0	0	0	0
OR2	0—20	0.8	0.1	0.1	0.6	0.8
OR2	20—40	0.5	0.1	0.1	0.4	0.6
OR2	40—60	0.2	0	0.1	0.1	0.4
OR2	60—80	0.1	0	0	0	0.3
OR2	80—100	0	0	0	0	0
RA1	0—20	0.5	0	0	0.5	0.6
RA1	20—40	0.2	0	0	0.1	0.3
RA1	40—60	0.1	0.1	0.1	-0.1	0.1
RA1	60—80	0	0.1	0.1	-0.1	0.2
RA1	80—100	0.1	0	0	0	0
TN1	0—20	0.6	0	0	0.6	0.7
TN1	20—40	0.2	0	0	0.3	0.5
TN1	40—60	0.1	-0.1	0	0.1	0.3
TN1	60—80	0	-0.1	0	0	0.1
TN1	80—100	0	0	0	0	0
TN2	0—20	0.6	0	0	0.5	0.7
TN2	20—40	0.3	0.1	0	0.2	0.4
TN2	40—60	0.1	0	0	0.1	0.2
TN2	60—80	0	0	0	0	0
TN2	80—100	0	0	0	0	0
UP1	0—20	0.5	0	0	0.5	0.5
UP1	20—40	0.2	0	0	0.2	0.3
UP1	40—60	0.1	0	0	0	0.2
UP1	60—80	0	0	0	-0.1	0.1
UP1	80—100	0	0	0	0	0
UP2	0—20	0.7	0	0	0.5	0.7
UP2	20—40	0.3	0	0	0.3	0.5
UP2	40—60	0.1	0	0.1	0.1	0.3
UP2	60—80	0	0	0	0	0.2
UP2	80—100	0	0	0	0	0
WB1	0—20	0.5	0	0	0.5	0.6
WB1	20—40	0.2	0	0	0.2	0.3
WB1	40—60	0	0	0	0	0
WB1	60—80	0	0	0	0	0
WB1	80—100	0	0	0	0	0
WB2	0—20	0.6	0	0	0.5	0.6
WB2	20—40	0.3	0	0	0.2	0.4
WB2	40—60	0	0	0	0	0

State-sector	Score Bins	Likelihood	Bias	Std. Err	95% conf. Interval	
WB2	60—80	0	0	0	0	0
WB2	80—100	0	0	0	0	0

Table 3.3: Poverty Lines at $ 1.25 PPP per capita per day in INR[17]

State (Sector)	Poverty Lines ($1.25 per capita per day in INR 2004-05 prices)		Poverty Lines ($1.25 per capita per day in INR 1999-2000 prices)
AP (Rural)	17.63		12.78
AP (Urban)	18.99		16.40
AS (Rural)	19.36		12.64
BI (Rural)	16.91		11.67
BI (Urban)	17.76		16.16
CH (Rural)	18.03		**
CH (Urban)	18.91		**
JH (Rural)	16.91		**
KA (Rural)	18.38		12.97
KA (Urban)	20.11		16.86
KE (Urban)	21.08		17.49
MA (Rural)	18.22		12.49
MP (Rural)	16.46		12.47
MP (Urban)	18.01		18.44
OR (Rural)	17.12		12.23
OR (Urban)	17.22		15.59
RA (Rural)	18.45		12.43
TN (Rural)	19.17		11.38
TN (Urban)	20.33		17.16
UP (Rural)	15.97		12.29
UP (Urban)	18.33		16.61
WB (Rural)	17.48		11.57
WB (Urban)	19.12		16.99

[17] The poverty lines used for creating scorecards based on Round 55 NSS are calculated using the ppp conversion factors published by World Bank for 1999-2000 and corrected for state-specific inflation using Consumer's Price Index (Agricultural Labourers) for the rural sector and Consumer's Price Index (Industrial Workers) for the urban sector. The price indices have been taken from www.labourbureau.nic.in. The poverty lines for scorecards based on the 61st Round (2004-05) have been taken from Schreiner (2008).

** These state sectors were unavailable during 1999-2000.

Table 3.4: Prediction of poverty rates % (households) using the scorecards (NSS rounds 61 and 62)

State_sector	Predicted in R61	Actual in R61	Deviation(%)	Predicted in R62	Actual in R62	Deviation(%)
AP1*	45	48	-3	41	43	-3
AP2	29	21	9	24	20	5
AS1*	52	53	-1	46	53	-6
BI1	62	67	-5	61	68	-7
BI2	37	33	4	39	44	-5
CH1	72	75	-3	71	80	-9
CH2	32	26	6	29	20	10
JH1	30	26	4	60	68	-7
KA1	59	62	-3	56	63	-7
KA2	27	22	5	26	20	6
KE2	22	16	5	19	14	5
MA1	50	52	-3	45	39	6
MP1	63	65	-3	62	62	0
MP2	35	31	4	29	23	6
OR1	73	76	-3	73	73	0
OR2	39	34	5	33	27	6
RA1	45	47	-2	41	38	3
TN1*	55	59	-4	52	47	5
TN2	33	22	11	32	17	15
UP1	45	47	-1	44	44	0
UP2	36	27	9	34	27	7
WB1	47	51	-4	46	52	-6
WB2	25	18	7	25	18	6

*Our scorecards can be applied directly to these 3 state sectors without any modification.
Deviation(%)=actual poverty ratio(%)-predicted poverty ratio(%)

Sector codes (1=rural, 2=urban)

Table 3.5: All India cell wise population (total)

	India (Total)			
	IL	JLG	SHG	Total
G1 (NGO)	159156	788856	59779457	60727469
G2 (NBFC)	501956	12747561	776921	14026438
G3 (Others)	41033	63791	122490	227314
Total	702145	13600208	60678868	74981221

Table 3.6: All India cell wise population (Rural)

	India (Rural)			
	IL	JLG	SHG	Total
G1 (NGO)	33088	498431	5.9E+07	5.9E+07
G2 (NBFC)	419763	9820023	773309	1.1E+07
G3 (Others)	33093	36221	110056	179370
Total	485944	1E+07	6E+07	7.1E+07

Table 3.7: All India cell wise population (Urban)

	India (Urban)			
	IL	JLG	SHG	Total
G1 (NGO)	126068	290425	866613	1283106
G2 (NBFC)	82193	2927538	3612	3013343
G3 (Others)	7940	27570	12434	47944
Total	216201	3245533	882659	4344393

Table 3.8: Sample breakup according to geography

State	Sample	Sample (%)	Districts	Rural	Urban	Rural(%)	Urban(%)
AP	5,725	39	11	3,145	2,580	54.93	45.07
AS	77	1	1	77	0	100.00	0.00
BI	172	1	4	117	55	68.02	31.98
CH	134	1	2	42	92	31.34	68.66
JH	79	1	2	79	0	100.00	0.00
KA	524	4	7	238	286	45.42	54.58
KE	132	1	1	0	132	0.00	100.00
MA	231	2	2	231	0	100.00	0.00
MP	541	4	6	348	193	64.46	35.54
OR	472	3	3	287	185	60.81	39.19
RA	245	2	2	245	0	100.00	0.00
TN	3,416	23	8	2,271	1,145	66.48	33.52
UP	558	4	7	512	46	91.76	8.24
WB	2,440	17	7	1,763	572	81.50	19.50
Total	14746	100	63	9,357	5286	64.90	34.10

Table 3.9: Sample breakup according to organizational and lending type

State	G1	G2	G3	IL	JLG	SHG
AP	1,793	254	3,678	1,569	1,760	2,396
AS	0	77	0	34	43	0
BI	86	86	0	32	140	0
CH	80	54	0	0	54	80
JH	0	79	0	0	39	40
KA	100	216	208	105	319	100
KE	132	0	0	0	0	132
MA	114	117	0	0	117	114
MP	453	88	0	0	359	182
OR	0	472	0	0	472	0
RA	95	150	0	0	74	171
TN	1,516	1,900	0	1,403	489	1,284
UP	299	259	0	42	516	0
WB	1,106	1,229	0	557	1778	105
Total	5,774	4,981	3,886	3,742	6,160	4,844

Table 3.10: Sample breakup according to the cells

	India (Total)			
	IL	JLG	SHG	Total
G1 (NGO)	268	2326	1908	4502
G2 (NBFC)	76	5669	613	6358
G3 (Others)	1674	597	1615	3886
Total	2018	8592	4136	14746

Table 4.1: Estimating Population poverty status from the sample *

	Poverty Status (Now)			Poverty Status (Before joining)		
Bins	Numbers	Likelihood	Number of "poor" in the sample	Numbers	Likelihood	Number of "poor" in the sample
0-20	35	55.27	19	224	55.27	124
20-40	390	30.87	120	509	30.87	157
40-60	299	5.76	17	109	5.76	6
60-80	116	3.90	5	19	3.90	1
80-100	26	0.80	0	5	0.80	0
	866		162	866		288
		Percentage below the threshold=	19.00%		Percentage below the threshold=	33%

*The calculations are only for G3-IL clients in Andhra Pradesh (rural)

Table 4.2: All India (net) movement (%)

	India (Total)			
	IL	JLG	SHG	Total
G1 (NGO)	2	9	12	12
G2 (NBFC)	0	10	18	12
G3 (Others)	14	12	14	26
Total	1	10	12	12

Table 4.3: All India poor clients (%)

	India (Total)			
	IL	JLG	SHG	Total
G1 (NGO)	22	34	29	29
G2 (NBFC)	4	22	30	20
G3 (Others)	17	18	24	8
Total	9	22	29	27

	India (Total)			
	IL	JLG	SHG	Total
G1 (NGO)	24	43	41	41
G2 (NBFC)	5	32	48	32
G3 (Others)	31	30	38	35
Total	11	33	41	39

Table 4.4: Rural (net) movement (%)

	India (Rural)			
	IL	JLG	SHG	Total
G1 (NGO)	-3	9	12	12
G2 (NBFC)	0	11	18	11
G3 (Others)	13	16	15	15
Total	1	11	12	12

Table 4.5: Rural poor clients (%)

	India (Rural)			
	IL	JLG	SHG	Total
G1 (NGO)	49	37	29	29
G2 (NBFC)	4	23	30	23
G3 (Others)	19	19	25	23
Total	8	24	29	28

	India (Rural)			
	IL	JLG	SHG	Total
G1 (NGO)	46	46	41	41
G2 (NBFC)	4	34	48	34
G3 (Others)	32	35	40	38
Total	9	35	41	40

Table 4.6: Urban (net) movement (%)

	India (Urban)			
	IL	JLG	SHG	Total
G1 (NGO)	3	9	11	17
G2 (NBFC)	1	8	0	8
G3 (Others)	17	6	7	12
Total	3	8	11	11

Table 4.7: Urban poor clients (%)

	India (Urban)			
	IL	JLG	SHG	Total
G1 (NGO)	15	30	11	8
G2 (NBFC)	7	17		17
G3 (Others)	9	17	15	11
Total	12	18	11	14

	India (Urban)			
	IL	JLG	SHG	Total
G1 (NGO)	18	39	22	25
G2 (NBFC)	8	25		25
G3 (Others)	26	23	22	23
Total	14	26	22	25

Table 4.8: State wise movements (all figures in %)

	Poor Now	Poor earlier	Movement	Rural Poor Now	Rural Poor Earlier	Rural Movement	Urban Poor Now	Urban Poor Earlier	Urban Movement
AP	19	37	18	21	41	20	12	23	11
AS	37	37	0	37	37	0			
BI	29	41	11	32	42	10	26	38	12
CH	19	26	7	22	30	8	10	14	4
JH	36	47	11	36	47	11			
KA	27	47	20	29	52	23	20	31	11
KE	15	22	6				15	22	7
MA	33	45	11	33	45	12			
MP	39	55	12	40	55	15	12	38	26
OR	37	45	9	41	51	10	28	32	4
RA	38	44	13	38	44	6			
TN	22	33	9	25	36	11	13	22	9
UP	30	32	2	33	35	8	42	45	3
WB	24	26	2	32	34	2	16	16	0

Table 4.9: District wise movements(all numbers in percentages)

District	State	Poor now	Poor earlier	Movemt	Rural Poor Now	Rural Poor when joined	Urban Poor Now	Urban Poor when joined
Mahamaya Nagar	UP	2	2	0	2	2		
Durg	CH	4	4	0	4	4		
Dewas	UP	5	14	9			5	14
Aligarh	UP	6	7	1	6	7		
Gulbarga	KA	8	30	22			8	30
Raipur	CH	12	16	4	20	27	7	9
Vizag	AP	12	20	8			12	20
Ujjain	MP	12	19	7	11	16	13	22
Chittoor	AP	13	27	14	17	36	12	25
Raichur	KA	13	14	1	13	14		
Gwalior	MP	14	27	14	23	28	6	27
Hoogly	WB	14	16	2	14	16		
Viluppuram	TN	14	24	10	15	25	7	18
Yadgir	KA	15	29	14	25	54	10	17
Adilabad	AP	15	25	10	15	25		
Hassan	KA	15	25	10	17	30	12	18
RangaReddy	AP	15	24	9	15	24	15	24
Cuddalore	TN	16	22	6	17	22	13	21
Hoshangabad	MP	17	28	11	17	28		
Vellore	TN	18	31	14	18	31	17	32
Mahboobnagar	AP	18	29	12	19	34	16	23
Chennai	TN	18	37	19			18	37
Ganjam	OR	18	28	10	18	28		
Kolkata	WB	19	18	-1			19	18
Anantpur	AP	20	28	8			20	28
Raisen	MP	21	33	12	21	33		
Thiruvallur	TN	22	27	5			22	27
Sikar	RA	22	36	14	22	36		
Thanjavur	TN	23	34	11	23	34		
Thrissur	KE	24	33	9			24	33
Warangal	AP	24	46	22	24	46		
Puri	OR	24	27	3			24	27
Tiruvanamalai	TN	24	37	13	24	37		
Tumkur	KA	24	42	17	23	42	28	40
East Godavari	AP	25	28	3	25	28		

District	State	Poor now	Poor earlier	Movemt	Rural Poor Now	Rural Poor when joined	Urban Poor Now	Urban Poor when joined
24 Pgns (North)	WB	25	29	4	31	34	20	24
Patna	BI	25	35	10	32	38	17	31
Haveri	KA	26	41	15			26	41
Nizamabad	AP	26	30	4	26	30		
Hazaribagh	JH	27	37	10	27	37		
Kanyakumari	TN	28	39	12	25	36	30	42
Khurda	OR	30	33	3	35	41	25	26
Nanded	MA	30	35	5	30	35		
Kishanganj	BI	31	41	10	31	41		
Howrah	WB	33	37	5	39	50	29	30
Alirajpur	UP	33	38	5	33	38		
Kurnool	AP	33	55	22			33	55
Nadia	WB	34	36	2	34	36		
Yavatmal	MA	35	44	9	35	44		
Saran	UP	37	46	9	49	54	27	39
Banswara	RA	38	47	9	38	47		
24 Pgns (South)	WB	39	38	-1	39	38		
Deoghar	JH	41	50	9	41	50		
Bardhaman	WB	42	47	5	42	47		
Bhabhua	BI	49	55	6	49	55		
Agra	UP	50	43	-7	49	42	55	52
Bhadohi	UP	53	54	1	53	54		
Mirzapur	UP	54	53	-1	54	53		
Ajamgarh	UP	55	54	-1	55	54		
Deoria	UP	55	52	-3	55	52		
Kamrup	AS	37	37	0	37	37		

Table 4.10: Client movements with years of association

Year	Current	Previous	Movement	Percentage Improvement	National poverty level estimates
2009	25%	28%	3%	11%	-
2008	24%	29%	5%	17%	25%
2007	26%	30%	4%	13%	19%
2006	24%	31%	7%	23%	17%
2005	22%	30%	8%	27%	28%
2004	21%	32%	11%	34%	20%
2003	22%	35%	13%	37%	19%
2002	23%	35%	12%	34%	19%
2001	19%	31%	12%	39%	23%
2000	30%	36%	6%	17%	19%
1999	24%	34%	10%	29%	26%
1998	33%	34%	1%	3%	32%
1997	34%	36%	2%	6%	34%
1996	45%	47%	2%	4%	34%
1995	35%	36%	1%	3%	35%

*Percentage improvement=Movement%/Previous percentage*100

Table 4.11: Household characteristics associated with movements

Geography	Household characteristics		Percentages moved
All India*	**Regular Salary**	Yes	23
All India	Regular Salary	No	12
All India	Graduate	Yes	16
All India	Graduate	No	14
All India	**Bank account earlier**	Yes	22
All India	Bank account earlier	No	12
All India	Bank account now	Yes	19
All India	Bank account now	No	10
All India	**Pucca house earlier**	Yes	20
All India	Pucca house earlier	No	10
All India	**Pucca house now**	Yes	20
All India	Pucca house now	No	8
Rural	Pucca house earlier	Yes	15
Rural	Pucca house earlier	No	6
Rural	Pucca house now	Yes	14
Rural	Pucca house now	No	5
Urban	**Pucca house earlier**	Yes	29
Urban	Pucca house earlier	No	18
Urban	**Pucca house now**	Yes	28
Urban	Pucca house now	No	14
Rural	Self employed in non agriculture		13
Rural	Agricultural Labour		9
Rural	Other labour		7
Rural	Self employed in agriculture		6
Rural	Others		17
Urban	**Self employed**		25
Urban	**Regular Wage/Salary**		30
Urban	Casual labour		13
Urban	**Others**		26

*Bold faced categories show the proportion of movement exceeding 0.2

Table 4.11: Movement estimates across round 1 and round 2 (validation samples only)

Sector	MFI	Organztn	Lend	Round 1 sample	Movement (round 1)	Round 2 sample	Movement (round 2)
Rural	MFI1	G1	JLG	211	7	128	1
Rural	MFI2	G2	JLG	199	2	159	6
Urban	MFI2	G2	JLG	75	0	200	-1
Rural	MFI3	G2	JLG	251	5	32	4
Urban	MFI4*	G2	JLG	330	11	90	1
Rural	MFI5*	G2	JLG	32	24	75	14
Rural	MFI6*	G2	JLG	364	11	102	6
Urban	MFI6	G2	JLG	336	7	160	5
Urban	MFI7*	G2	JLG	59	22	41	1
Rural	MFI8	G2	JLG	793	10	135	12
Urban	MFI8	G2	JLG	134	11	148	13
Rural	MFI9	G2	SHG	483	17	130	24
Rural	MFI10	G3	IL	372	17	548	64
Urban	MFI10	G3	IL	181	7	573	49
Rural	MFI10	G3	JLG	169	16	193	26
Urban	MFI10	G3	JLG	120	7	115	9
				4109	11%	2829	9%

*MFIs marked with asterisks show significant upward bias (for G2-JLG) in round 1.

Appendix B: Figures

Figure 4.1 : Household distribution of Number of Dependents

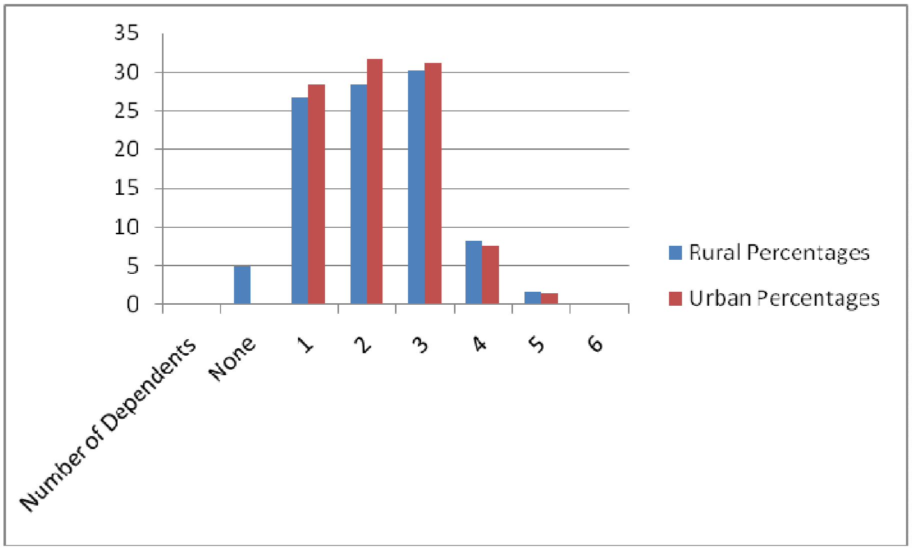


Figure 4.2: Household distribution of size

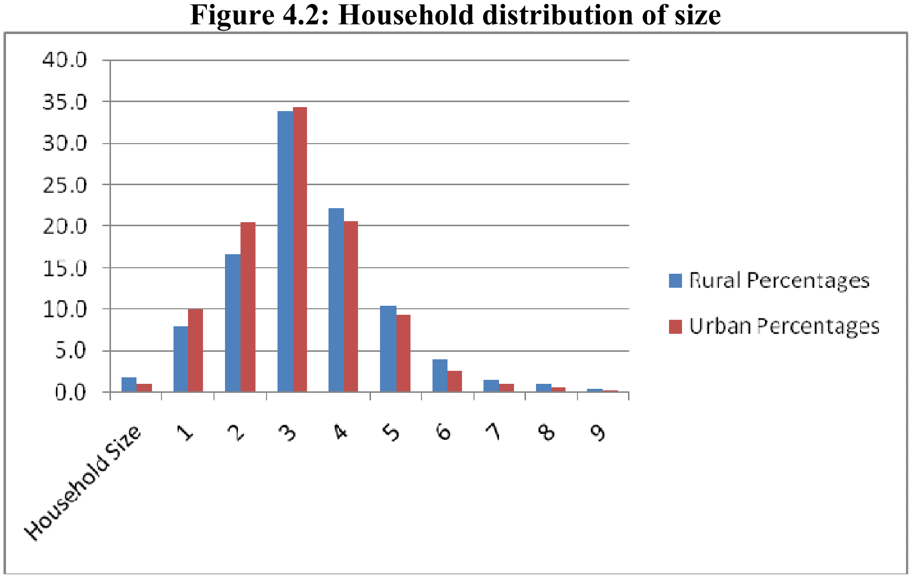


Figure 4.3: Household distribution of Education status (household head)

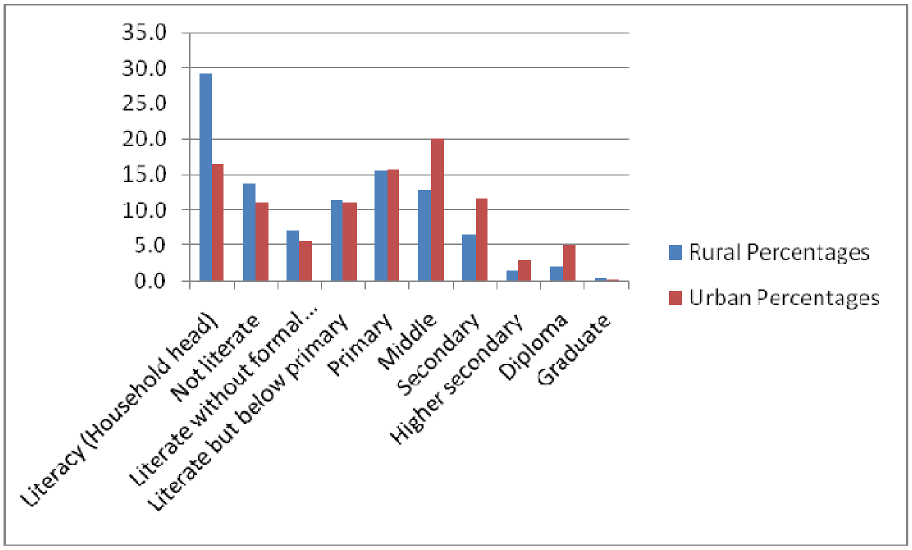


Figure 4.4: Household movement and poverty status

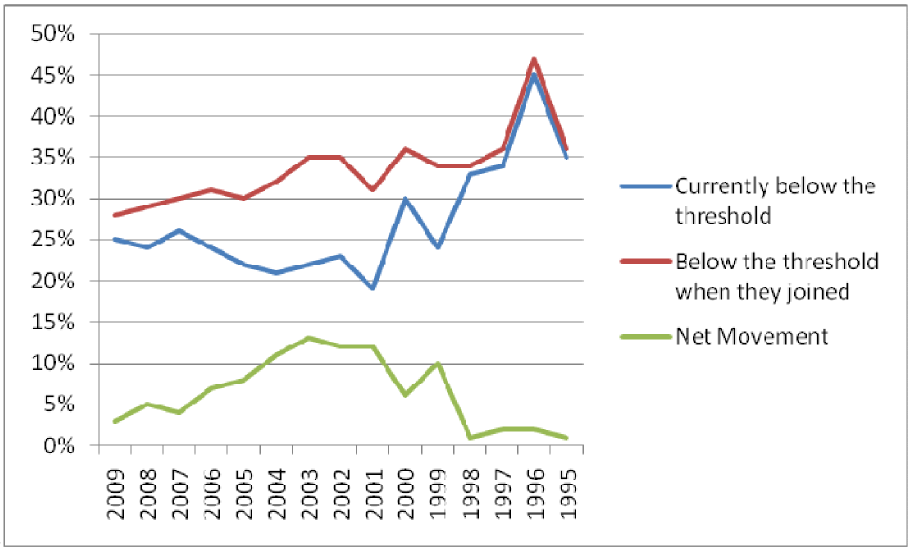


Figure 4.5: Poverty status of MFI clients versus national poverty level (HCR)

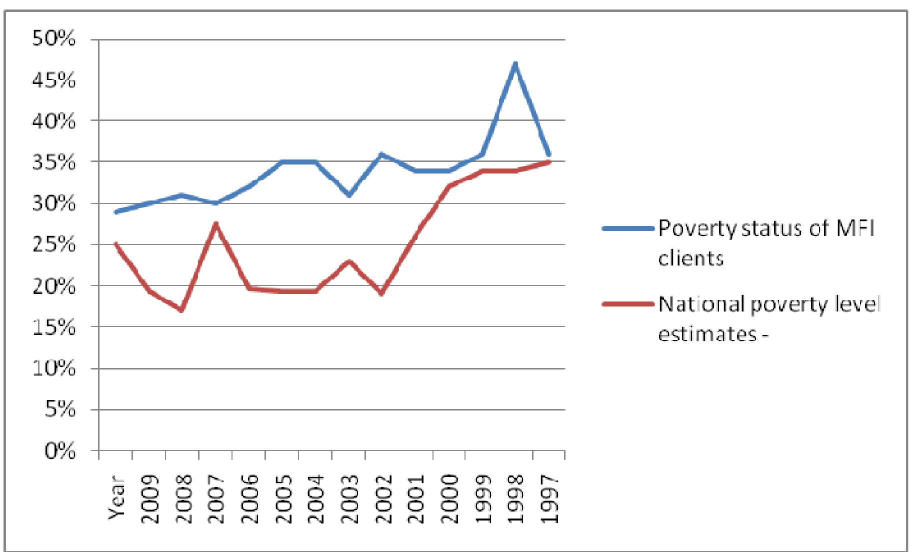
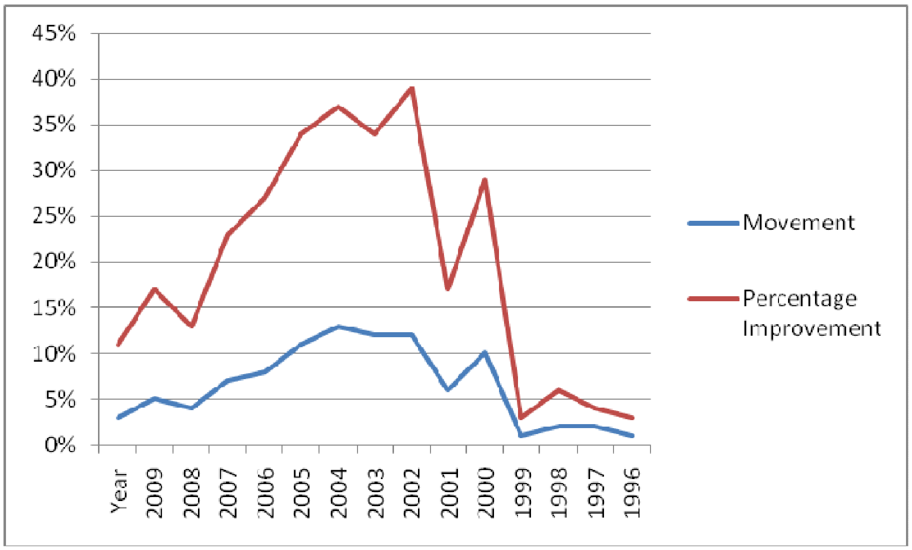


Figure 4.6: (net) movement of clients



APPENDIX C: QUESTIONNAIRE

RURAL	
URBAN	

Lending Code [ ]

Questionnaire No. | | | | | | | | | |

IDF SURVEY on MFI CLIENTS

[0] descriptive identification of sample household	
1. State.:	6. Village/Town Name:
2. District:	7. Name of head of household:
3. Tehsil/Town:	8. Name of informant:
4. Panchayat name:	9. Name of the MFI:
5. Ward/inv. unit/block:	10. MFI client since (Year Only):

[1] identification of sample household

item no.	item	code
1.	response code	
2.	survey code	
3.	reason for substitution of original household (code)	

CODES FOR BLOCK 1

*Item 1: **response code** : informant: co-operative and capable -1, co-operative but not capable -2, busy -3, reluctant - 4, others 9*

*Item 2: **survey code** : original – 1, substitute – 2, casualty – 3*

*item 3: **reason for substitution of original household** : informant busy -1, members away from home -2, informant non-cooperative -3, household no longer staying-4, others – 9*

** tick mark (✓) may be put in the appropriate place.*

[2] particulars of field operations

srl. no.	item	investigator			assistant superintendent			superintendent		
(1)	(2)	(3)			(4)			(5)		
1.	i) name (block letters)									
	ii) code									
2.	**date(s) of** :	DD	MM	YY	DD	MM	YY	DD	MM	YY
	(i) survey/inspection									
	(iv) despatch									
3.	signature									

[3] household characteristics			
1. Household Size		8. Primary source of energy for lighting (Code)	
2. Household Type		8.1 Since when have you been using this as primary source of energy for lighting (Code)	
3. Religion (Code)		9. Is any member of the household a regular salary earner (yes-1, no-2)	
4. Social Group (Code)		9.1 Annual family income (in Rupees)	
5. Whether owns any land (yes-1, no-2)		10. Does the household possess ration card (yes-1, no-2)	
6. If yes in item 5, type of land owned (Code)		11. If yes in item 10, type of ration card (code)	
7. Primary Source of energy for cooking (code)		12. During the last 365 days whether any member of the household is a NREGA beneficiary? (yes-1, no-2)	
7.1 Since when have you been using this as primary source of energy for cooking (Code)		13. If no in item 12, reasons. (code)	

CODES FOR BLOCK 3

item 2: ***household type*** *:* ***for rural areas****: self-employed in non-agriculture-1, agricultural labour-2, other labour-3, self-employed in agriculture-4, others-9*

for urban areas*: self-employed-1, regular wage/salary earning-2, casual labour-3, others-9*

item 3*:* ***religion*** *: Hinduism-1, Islam-2, Christianity -3, Sikhism-4, Jainism-5, Buddhism-6, Zoroastrianism-7, others-9*

item 4*:* ***social group*** *: scheduled tribe-1, scheduled caste-2, other backward class-3, others-9*

item 6*: Type of land owned: homestead only-1, homestead and other land-2, other land only-3*

item 7*:* ***primary source of energy for cooking*** *: coke, coal-01, firewood and chips-02, LPG-03, gobar gas-04, dung cake-05, charcoal-06, kerosene-07, electricity-08, others-09, no cooking arrangement-10*

item 7*.1* ***and 8.1:*** *Duration of usage of the primary source of cooking: 1-2 yrs -1, 2-5 yrs -2, more than 5 yrs-3*

item 8*:* ***primary source of energy for lighting*** *: kerosene-1, other oil -2, gas-3, candle-4, electricity-5, others-9, no lighting arrangement-6*

item 11*:* ***ration card type****: Antodaya -1, BPL – 2, others – 3*

item 13*:* ***reasons****: do not need -1, not aware – 2, tried but did not get – 3, others---4*

[4] household characteristics

srl. no.	*Name of Member*	*Sex (Male-1, Female-2)*	*Age (Years)*	*Marital Status (code)*	*General Educational level (code)*	*Relation to household head (code)*
(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*

CODES FOR BLOCK 4

Col.(5) : ***marital status:*** *never married – 1, currently married – 2, widowed – 3, divorced/separated – 4*

Col. (6) : ***general educational level:*** *not literate –01, literate without formal schooling –02, literate but below primary –03, primary –04, middle –05, secondary –06, higher secondary –07, diploma/certificate course – 08, graduate - 10, postgraduate and above -11*

Col. (7) : ***relation to household head:*** *self-1, spouse of head-2, married child-3, spouse of married child-4, unmarried child-5, grandchild-6, father/mother/father-in-law/mother-in-law-7, brother/sister/brother-in-law/sister-in-law/other relatives-8, servants/employees/other non-relatives-9*

[5] assets possessed just before you joined MFI
****(investigator: The effective date of entering 'MFI' is as entered in 0.10)**

Code	Assets	Whether possessed or not (yes…1, No…2)
1	bedstead	
2	almirah, dressing table	
3	chair, stool, bench, table	
4	suitcase, trunk, box, handbag and other travel goods	
5	foam, rubber cushion (dunlopillo type)	
6	carpet, daree & other floor mattings	
7	other furniture & fixtures (couch, sofa, etc.)	
8	radio	
9	television	
10	VCR/VCP/DVD	
11	camera & photographic equipment	
12	tape recorder, CD player	
13	musical instruments	
14	electric fan	
15	air conditioner	
16	air cooler	
17	lantern, lamp, electric lampshade	
18	sewing machine	
19	washing machine	
20	pressure cooker/pressure pan	
21	refrigerator	
22	electric iron, heater, toaster, oven & other electric heating appliances	
23	bicycle	
24	motor cycle, scooter	
25	motor car, jeep	
26	clock, watch	
27	other machines for household work	
28	personal computer	
29	mobile phone handset	
30	All Pucca Residence	

[6] Finances	
1. Do you have a bank account *(yes…1, No…2)*	
2. Did you have a bank account before you joined MFIs *(yes…1, No…2)*	
3. Have you invested in jewelleries *(yes…1, No…2)*	
4. Did you invest in jewelleries before you joined MFIs*(yes…1, No…2)*	

[7] assets possessed now

Code	Assets	Whether possessed or not (yes…1, No…2)
1	bedstead	
2	almirah, dressing table	
3	chair, stool, bench, table	
4	suitcase, trunk, box, handbag and other travel goods	
5	foam, rubber cushion (dunlopillo type)	
6	carpet, daree & other floor mattings	
7	other furniture & fixtures (couch, sofa, etc.)	
8	radio	
9	television	
10	VCR/VCP/DVD	
11	camera & photographic equipment	
12	tape recorder, CD player	
13	musical instruments	
14	electric fan	
15	air conditioner	
16	air cooler	
17	lantern, lamp, electric lampshade	
18	sewing machine	
19	washing machine	
20	pressure cooker/pressure pan	
21	refrigerator	
22	electric iron, heater, toaster, oven & other electric heating appliances	
23	bicycle	
24	motor cycle, scooter	
25	motor car, jeep	
26	clock, watch	

[7] assets possessed now		
Code	Assets	Whether possessed or not (yes…1, No…2)
27	other machines for household work	
28	personal computer	
29	mobile phone handset	
30	All Pucca Residence	

APPENDIX D: LITERATURE REVIEW

D.1. Literature Survey on MFI

The literature on microfinance can be divided into two distinct areas. While, theoretical models focus mostly on the efficiency of the joint liability lending contracts, the empirical literature looks at performance of the MFIs both in terms of the loan recovery rates as well as improving socio economic conditions of the MFI clients.

The early theoretical modelling of MFIs began with Ghatak (1999), Morduch (1999), Ghatak and Guinnane (1999), Ghatak (2000). These models are based on adverse selection (Stiglitz and Weiss, 1981) where the borrowers' (MFI clients') credit worthiness is unknown to the MFI but known to the borrowers. In these models, the borrowers know the risk of the projects they undertake, while the lenders have an idea of the probability distribution of the riskiness of the projects. These models show that, with peer selection and joint liability contracts, default rates are low and aggregate welfare is maximized. Joint liability lending works as follows: borrowers, who work on independent projects, self-select into groups to get the loan. If the group does not fully repay its obligations, then MFI cuts off all members from future credit until the debt is repaid. Joint liability induces borrowers, who have perfect information about the type of each other, as they belong to small rural communities, to choose partners of the same type: this is called peer selection. The repayment rates are high with joint liability and peer monitoring because it is now incentive compatible for the group members to monitor each other. However, Gangopadhyay et al (2005) argue that, the result is obtained because of a curious case that, in the absence of a constraint that puts an upper limit on the amount to be repaid, in the event of a default by any group member, the group members may effectively hide such defaults. They would prefer to declare "no default" (with a side payment to the defaulting member) than pay up the penalty. However, if an adequate constraint is put in place, joint liability contracts continue to have high repayment rates. They show that what really drives the result is co-signing contracts. In particular, they show that the equilibrium co-signing debt contract strictly Pareto dominates equilibrium without a co-signer especially if the latter entails credit rationing.

The empirical literature on MFIs can be divided into two distinct areas-supply side issues and demand side issues. Supply side issues involve studies that focus on the effectiveness of various MFI contracts in terms of repayment, return on assets (ROA) etc. On the demand side, the impact on households is measured.

There has been more work done on the demand side. However, the impact of MFIs on household level poverty alleviation is varied. One of the early poverty impact studies of MFIs is in Hulme (2000). They use village wise aggregate data for countries in Asia. They employ a control group approach looking at the changes in income for households in villages with microfinance programs as against changes for similar households in non-program areas. In general, a positive impact is found on borrower incomes of the poor. Their incomes over the control group had increased (1988-1992) ranging from 10-12% in Indonesia to around 30% in Bangladesh and India. Interestingly, they find that the gains are larger for non-poor borrowers. Another major early initiative that has provided some of the empirical work are the surveys conducted in the 1990s by the Bangladesh Institute of Development Studies (BIDS) and the World Bank. These surveys provided the data for several major analyses, such as Pitt and Khandker (1998), Khandker (2003). The former study finds that the MFI programmes have positive effect on household consumption, which is significantly greater for female borrowers. Khandker (2003) follows up this earlier work by employing panel data. He used the BIDS and World Bank survey conducted in 1998-99 and traced the same households from the 1991-92 survey. He found that MFI activities have positive impact on consumption.

However, there are examples of many other studies that are either inconclusive or provide less convincing results. Coleman (1999) focuses on experiences with village banking in Thailand. The paper uses data on villages that had participated in village bank microfinance schemes and those control villages that were designated as participants, but had not yet participated. This approach compares the variance between income for participants and non-participants in program villages with the same difference in the control villages, where the programs were introduced later. From the results obtained in their study, the poverty impact of the schemes appears highly dubious. Months of village bank membership have had no impact on any asset or income variables and there is no evidence that village bank loans were directed to productive purposes. The small sizes of loans mean that they were largely used for consumption, but one of the reasons there is a weak poverty impact is that there was a tendency for wealthier households to self-select into village banks.

Coleman (2006) uses the same survey data but reconsiders the estimation strategy to control for self-selection. He argues that the village bank methodology, which relies on self-selection by loan size and monitoring by frequent meetings, may not reach the poorest. This is so because many wealthy households tend to be on village bank committees and the failure to control for this leads to systematic biases. The regression results of Coleman (2006) indicate that there is a substantial difference between ordinary members and committee members of village banks. The impact of micro credits on ordinary members' wellbeing is either insignificantly different from zero or negative. On the contrary, the impact of microfinance programs on committee members' measures of wealth, income, savings, productive expenses and labour time is positive. A similar result in terms of rationing micro credit in favour of better-off groups or members is found by Doung and Izumida (2002) in a study of six villages in Vietnam.

Chen and Snodgrass (2001) examine the operations of the Self Employed Women's Association (SEWA) bank in India, which provides low-income female clients in the informal sector with both saving and loan services. The study tests for the impact of these services by comparing the bank's clients against a randomly selected control group in a similar geographic area. Two surveys were conducted two years apart. Average incomes rose over time for all groups—borrowers, savers and the control—although the increase was less for the latter. In terms of poverty incidence there was little overall change, although there was substantial 'churning', in that amongst the clients of SEWA there was quite a lot of movement above or below the poverty line. In interpreting these results Meyer (2002) argues that the evidence on the counterfactual is not strong enough. That is, they argue that what would have happened to the clients in the absence of the services of SEWA, is not sufficiently strongly established to draw any firm conclusions on poverty impact. The smoothing of consumption over time to protect the poor against adverse shocks is one of the principle objectives of micro credit. Similar study was done for Bangladesh by Amin et al. (2003). They compute several measures of vulnerability. However, they do find that the decision to join or the clients being invited to join) a microfinance program is highly endogenous. In a two village experiment, they do not find strong evidence that the vulnerable population is indeed catered to by the MFIs. The vulnerable are more likely to join a micro credit program in only one of the two villages. Further, for the vulnerable below the poverty line in one village, there is no evidence that there are more likely to be members of a program, and in the other village there is evidence that they have either chosen not to join or are actively excluded, presumably on the grounds that they are a poor credit risk. Hence the very poor and vulnerable do not appear to be reached. Some positive conclusions in terms of the ability of micro finance to reduce vulnerability are found for Indonesia by Gertler et al (2003). They find that micro finance helps households to smooth consumption in the face of declines in health of adult family members. An excellent survey on MFI effects on its clients in Asia is provided in Kurmanalieva et al (2003).

In India, there is another model of SHG lending that is extremely prominent. It is the SHG bank linkage programme. The empirical evidence on microcredit arising out of SHG linkages to banks suggest a considerable improvement in the economic status of the households. These SHG bank linkage initiatives are different from the usual MFI lending models.

The most common linkage model in India is where the banks deal directly with individual SHGs. Usually; they do so through an intermediary NGO. These NGOs act as financial intermediary between the banks and the SHGs by accepting contractual responsibility for repayment of the loan to the bank. Therefore, the NGOs help the bank in identification, preparation of loan application, monitoring, supervision and recovery of loans while it helps the SHG by providing the initial training, guidance to rural poor in organizing themselves into thrift and credit groups. These SHGs are formed and supported usually by NGOs or (increasingly) by Government agencies. These SHGs are linked not only to banks but also to wider development programmes, SHGs are seen to confer many benefits, both economic and social. SHGs enable women to grow their savings and to access the credit which banks are increasingly willing to lend. SHGs can also be community platforms from which women become active in village affairs, stand for local election or take action to address social or community issues. These SHGs have typically between 10-15 members (EDA-APMAS 2006).

Aghion & Morduch (2000) find that the concept of forming SHGs and linking them to banks, reduce poverty by raising incomes and broaden financial markets by principally providing credit, to small scale entrepreneurs. Littlefield, Morduch and Hashemi (2003) and Cheston and Kuhn (2002) find such SHG linkages also lead to women's empowerment. Puhazhendhi and Satyasai (2000) carried the first study of NABARD on SHG-bank linkage programme. The study assessed the impact of microfinance on socio-economic conditions of 560 household members from 223 SHGs located in 11 states; Rajasthan (Northern region), Orissa and West Bengal (Eastern region), Madhya Pradesh and Utter Pradesh (Central region), Gujarat and Maharashtra (Western region), and Andhra Pradesh, Karnataka and Tamil Nadu (Southern region). They find that, 84 per cent belonged to the economically weaker sections, which were homogenous in terms of group members living in the same village or having uniform socio-economic status. They find a significant improvement in economic status of the households in terms of increased savings and increased average value of assets per household (including consumer durables and livestock). In another study on SHG Linkage Programme in India, by Puhazhendi and Badatya (2002) assessed the impact on SHG members in three eastern states, i.e., Orissa, Jharkhand and Chattisgarh. The findings were similar to the earlier one in terms of socio economic improvements.

The study by EDA-APMAS (2006), which in scope was quite distinct from the earlier studies, addressed a wide range of issues including cases of dropouts from SHGs, and issues of social harmony and social justice, community actions, book-keepings, equity, defaults and recoveries and sustainability of SHGs. The study was based on a survey of 214 SHGs in 108 villages in 9 districts of four states, two southern (Andhra Pradesh and Karnataka) and two northern (Orissa and Rajasthan). The study provides excellent documentation of the processes that are followed within the organization as well among the SHG members.

In a recent study, NCAER (2008) assessed the impact and sustainability of SHG bank linkage on the socio-economic conditions of the individual members and their households in the pre-SHG and post-SHG scenarios. This study was conducted for India as a whole covering six states Andhra Pradesh, Karnataka, Maharashtra, Orissa, Uttar Pradesh and Assam. They find that the bank linkage programmes has significantly improved the access to financial services of the rural poor and has had considerable positive impact on the socio-economic conditions and the reduction of poverty of SHG members and their households. It has also reportedly empowered women members substantially and contributed to increased self-confidence and positive behavioural changes in the post-SHG period as compared to the pre-SHG period.

The above studies, although elaborately documents the socio economic improvements of MFI clients, does not attribute these improvements to the MFIs alone. The difficulty in attributing the role of MFI in improvement of economic status of MFI clients vis-a-vis non MFI clients is the one of self-selection. One, MFIs select areas where they want to operate and two once an area is selected, people self-select them to join MFIs. It is likely, therefore, to presume that those who choose to join MFIs could be on different trajectories even in the absence of microfinance. This invalidates comparisons over time between clients and non-clients. The appropriate framework for analysis would be through randomized trials. Recently, Banerjee et-al (2009), does a randomized trial to establish the impact of Micro credit on household economic status. They find that micro credits do have important effects on business outcomes as well as on the composition of household expenditure. While microcredit affects household expenditure, creates and expands new businesses, it appears to have no discernible effect on education, health or women empowerment at least in the short-term (within 15-18 months), which was the study period.

Our current study is not an ‘impact evaluation’ study. That is, we do not explicitly ask the question “what impact does MFIs play in improving the socio economic conditions of the

MFI clients?" Instead we ask, how many households, who are MFI clients, have crossed (from below) the USD 1.25 a day consumption threshold. Indeed, what part of such movements can be attributed to the role of the MFIs cannot be answered in the current study. However, what we will do is identify the factors that are common across three 'comparable' groups off clients. These groups are (a) all those who moved from below to above, (b) all those who moved from above to below and (c) all those who have not moved at all. What makes these groups comparable are (i) the type of MFI lending and organization they are exposed to (this will make the groups comparable according to the organizational and lending type), (ii) the geographical regions (this will make the groups comparable across local cultural and other idiosyncrasies) and (iii) the sectors (this will ensure the groups are comparable within rural or urban households). In a later study, we plan to do an impact evaluation study involving the MFI clients (treatment group) and non MFI clients from the same Geographical cluster (control group). However, many of our findings corroborate some of the earlier findings.

D.2. Literature survey on scorecards

The approach of creating scorecards based on observable characteristics from an already available source to speculate about the welfare levels of people originated in two separate yet complementary strands of literature –the literature on credit scorecards and that on proxy means tests for efficient targeting of welfare schemes.[18]

Use of discriminant analysis by Fisher (1936) to classify IRIS varieties engendered a methodology which was used by a plethora of analysts in post-war US to classify bad loans from good loans. One of the early scorecards developed and still used extensively is Altman (1968). The technique soon found widespread use in credit risk assessment. Altman (1968) studied set of firms that went bankrupt in Latin America and used linear discriminant analysis to classify them into two groups- safe and risky. Two benchmark scores were derived such that firms above the high benchmark score were "safe", firms below the low benchmark score were "risky", and those which lied in between were indeterminate. Building on the Altman Z score, with improved computing capacity and newer classification methods, credit analytics as a separate discipline on its own had started (Hand and Henley,1997). Statistical models called scorecards or classifiers, use predictor variables from application forms and other sources to yield estimates of the probabilities of defaulting. The statistical methods used in the industry are linear regression, logistic regression and decision trees along with discriminant analysis. Some of the texts detailing the various credit scoring methods and the problems inherent are Lewis (1992), Thomas et al (1992), Hand and Henley (1997), and Thomas (1998) etc. Apart from these specialised texts, there is a lot of general literature on classification algorithms and data mining (Hand, 1981, 1997).

We shall focus on the literature on proxy means tests in some detail below as this strand of literature, is in the lines of our exercise. What is worth noting is that the basic approach was informed by developments in credit scorecards. In particular, the spread of MFIs and micro-

[18] Another strand of literature, somewhat similar to this exercise (but will not be touched here) are the techniques of "small area estimation" which also use non-income variables in a census (or pseudo-census) to predict the poverty status at more granular levels of spatial/administrative aggregation than is possible through large-scale surveys like NSS consumption rounds

lending in developing countries necessitated use of non-income variables for proxy-ing the credit-worthiness (means) of individuals. Here, the aim is to target as many poor people as possible for inclusion in credit schemes through various instruments specially designed for the sector. This brought in a requirement of adapting credit scorecards to the developing country settings and establishing a direct connection between the two strands of literature.

Proxy means tests arose due to a need to create means tests that can be used as targeting procedures in the welfare schemes. If the exact per capita consumption levels or some such unambiguous welfare level of the target population were available, selecting the individuals becomes a simple means test. That is to say, the determination of whether a person has the means to a certain quality of life can be inferred directly in the presence of such information. As it often happens, we do not have information on the welfare levels of the people involved and thus have to resort to a proxy for the welfare levels. The name "proxy means test"[19] signifies use of welfare level information contained in large scale nationally representative consumption surveys to create rules using which one can approximate the welfare level of a suitable target population. Then classification of the population into groups that need intervention and groups that do not need it is done and the scheme targets the "needy" group.

A large number of proxy tests exist in the literature using a variety of statistical techniques. Grosh and Baker use consumption expenditure rather than income as the welfare measure for development off their proxy tools. In their simulations over household level data from Peru, Bolivia and Jamaica, they have used OLS regression techniques to generate weights for the household characteristics. The criteria used for evaluation of models in their article were "leakage" and "under coverage".[20] This approach has been followed in a large number of other studies where OLS regression was used for predicting consumption expenditure levels with different combinations of variables. Well known examples are Ahmed and Bouis (2002) for targeting food a subsidy program in Egypt.

Other statistical techniques that have been used for developing scorecards are linear probability models (IRIS centre, 2005), principal components analysis (PCA) (Ficha CAS system, Chile), logit/probit models (Schreiner, 2010) and quantile regression techniques (IRIS centre, 2010). Apart from the algorithms discussed above, there are procedures where a poverty minimising problem is solved with a given budget and information set (eg. Ravallion and Chao, 1989) and Glewwe, 1990) to derive weights for the variables included in the scorecards.

We have used a logit regression procedure for endogenously predicting weights for the household characteristics in our scorecards. We have used a score card method that is similar to Schreiner (2008) with important differences in the way validation and calibration was carried out. The way the models were built were completely based on a step-wise procedure without any likelihood calibration. We had initially aimed to 'identify' individual households who were poor and see if there is any significant change (vis-à-vis a cutoff) in the predicted probabilities of the household during the recall and the current period. Hence, the calibration

[19] Grosh and Baker (1995) define proxy means as "…a situation where information on household or individual characteristics correlated with welfare levels is used in a formal algorithm to proxy household income." (p. ix)
[20] Leakage errors are errors where true poor are incorrectly predicted are nonpoor and undercoverage errors occur when true nonpoor incorrectly predicted as poor.

was at the level of cutoffs, so adjusted that we catch 90% of the poor households. The models were built using the samples from NSS state-sectors completely. The validation was based entirely on bootstraps unlike the three-fold division of samples into train, test and calibration samples followed by Schreiner (2008). This approach allowed us to use the entire sample for model building.

APPENDIX E: SAMPLING FRAMEWORK

E.1 Introduction

We divided the country into rural and urban sectors. This was done primarily to capture the sector specific factors that might affect movements. We ensured that sufficient spread in terms of geography as well as MFI types was considered. Therefore, the

Note that, it takes some time for households to move across the threshold and clients who have taken loans more recently are less likely to have crossed the threshold than those who have taken, or have been taking, loans for a longer duration. We are here assuming that the current distribution of clients is the same as the cumulative distribution of clients over time in each state, region and by MFI. When we are looking up client lists, we should give greater weight to those who had become members further back in time, compared to the more recent ones. However, given that past members may be more difficult to trace compared to the current ones, we will have to make some adjustments, depending on the particular state and MFI client list we are using.

E.2 Survey

The design of the survey began in May 2010. The design of the survey involved the following stages- (a) identifying the MFIs who would be part of our study (b) selecting the sample of households to be surveyed (c) conducting the household interviews.

Selecting MFIs

To draw the list of MFIs who would be part of our study, we partnered Sa-Dhan (www.sadhan.net). From the MFIs that are associated with Sa-Dhan, we approached 232 of them to be part of the study. While selecting the MFIs for our study, we approached only those MFIs who had started their operations on or before 2008. This was necessary as we believe that for any client to move from below the USD 1.25 a day consumption level to above it; it would need a minimum of three years to do that. Out of all the 37 MFIs who fulfilled the year of inception criteria and agreed to participate, finally only 27 MFIs could be part of our study. However, we ensure that the MFIs who participated were sufficient to give us, at an all India level, the estimates for all the 9. However, we could not get the data from the sole NBFC MFI that practise SHG lending model and operating in urban India.[21] Therefore, the MFIs we have selected populate the remaining 17 cells (9 in rural and 8 in urban) across India. Out of these 27 MFIs, 16 belonged to Group 1, 8 belonged to Group 2 and 3 belonged to Group 3. In terms of lending types, 6 MFIs were involved in Individual

[21] This means we have lost a total of 3602 observations from the population of 76 million.

Lending, 15 MFIs practiced joint liability lending while 8 followed the SHG model. In terms of Geographical operations, 17 MFIs operated in only one State while the remaining 10 MFIs operated in more than one State. The cell wise distribution of these MFIs is given in table 2.5.

The sample included clients from 27 MFIs. These MFIs cover all the 14 states and have a total client base of 81,29,687. Approximately 84% of the clients were rural based and 16% were urban based. The total number of clients covered by the MFIs in our sample constituted about 11% of total MFI client across India. The respective rural and urban shares were 36.7% and 35.7%. The number of clients each of these 27 MFIs serve is presented in Table 2.6.

Apart from these, we surveyed 7 SHG-BLPs. These were drawn from the rural areas of Rajasthan, Maharasthra, Tamil Nadu, West Bengal and Madhya Pradesh.

Drawing the samples per cell

For a State, we first calculated the total number of clients we will be sampling. We then divided the total number equally across the 18 possible cells ensuring in the process that no cell shall have less than 40 clients who will be surveyed. Although we need a minimum of 30 observations per cell for any meaningful statistical inference, we sampled 40 per cell in order to be sure that, even if we 'loose' some observations, we will be left with sufficient observations. We had to divide the sample size for a state equally among the possible cells, because we had no disaggregated secondary data about (a) state wise breakup for all the MFIs in India if they were operating in more than one state and (b) lending type wise break of all the MFIs in India who were following more than one kind of lending models and (c) rural urban break up of clients per state per lending type for the MFIs who either operated in multiple states or followed more than one type of lending. Once the number per cell was arrived at, we divided them equally across the "agreed MFIs" for this cell. However, we ensured that for any given cell, we will have at least 40 clients from a single MFI. This is because, if eventually the other agreed MFIs could not be part of the study[22], data from the existing MFI would be sufficient for statistical inference.

Calculating the sample size per MFI per cell

While selecting the number of samples to be drawn per MFI for a given cell, we used the following filters to draw the eventual sample

(a) For no MFI, will we select less than 40 clients
(b) No clients who joined in 2010 is considered
(c) No clients who joined before 1990 are considered.

[22] Note that 10 out of the 37 MFIs had initially agreed but finally could not be part of the study.

Once the sample size per MFI per cell is determined, we proceed to draw the exact samples. We do that by sequentially determining the following. First, the districts, second the branches and third the clients.

Selecting districts

For a given MFI that operates in the particular cell, only those districts are considered for studying where either the MFI is

(a) operating for at least 5 years (that is operating before 2005) if the MFI is operational pre 2005; or
(b) operating since the day of inception for the MFI if the MFI has started operation post 2005.

In case the MFI has started operation on or after 2008, we ignore the MFI from our study.

Using criteria (a) and (b), we narrow our sampling framework down to N districts. We choose up to 2 districts from N. However, if the total number of clients to be selected for a MFI is less than equal to 50, we will select only one district. This wasdone for operational ease (to limit the study up to two districts) and efficiency (to save on the fixed costs from spreading across districts if the eventual sample size from the districts is low). The number of clients that are surveyed per district is arrived at by using proportional sampling.

Once the districts are selected for a State, we then proceed to select the branches from these districts.

Selecting the branches

Although there is no universal rule, usually MFIs have on an average 3500 clients per branch. Once, the client size exceeds that number, they open a new branch transferring some of the excess clients from the current branch. As some of our survey was done by the enumerators who were the Field officers (employees) of the concerned MFI, we had to ensure that the number of surveys per enumerator did not exceed a manageable size.

From the two districts selected, only those branches qualify for selection that is

(a) operating for at least 5 years (that is operating before 2005) if the MFI is operational pre 2005; or
(b) operating since the day of inception for the MFI if the MFI has started operation post 2005
(c) no MFI whose branches have started on or after 2009 is considered.
(d) has at least 40 clients.

Selecting sample size per branch

Once, the branches were selected, we used a simple rule to select number of clients per branch based on operational efficiency.
The number of branches to be selected in all, denoted by B is given in the table below.

Cell sample size for a MFI	No. of Branches
30*-40	1
41-80	2
81-120	3
121-160	4
161-200	5

Selecting Households

Once the sample size from a branch is determined, we proceed to draw the client list from the branch level data. As we believe that for a household who is associated longer with a MFI, it is more likely that a household will cross the USD 1.25 consumption threshold from below we give clients who are there for a longer duration higher weights than those who are there for shorter durations.

Therefore, from the branch selected, we look at the client list of all current clients and find out for how long they are there with the MFI. We gave higher weights to older clients while selecting the random sample.

Enumerators

For the survey, we appointed 7 State coordinators (each coordinator looking after 2 states each) who were responsible for conducting the surveys in the states. The coordinators were responsible for training the enumerators, coordinating with the MFIs, coordinating the activities on ground, distributing and collecting questionnaires etc. There were two types of enumerators. For certain MFIs, all the enumerators were independent while for many MFIs, the enumerators were the field staffs of the MFIs. The reason for involving the field officers from the MFIs as enumerators were (a) reluctance on the part of most MFIs to share their client details with outsiders and (b) operational efficiency, as the field officers knew the local areas better. However, the MFIs were told that an extensive validation will be done in round 2. Therefore, the survey was conducted in two rounds. The first round of household interviews were conducted between June-November, 2010. We interviewed a total of 11,137 households in all during this period. Except Assam, all the states were covered in this round. Round 2 of the survey started in November 2010 and concluded in February 2011. In this round we carried validation of round 1 survey, along with first time survey in Assam and of SHG Bank linkage clients.[23] The total number of surveys done in this round is 4,168. The

[23] The round 2 surveys (including the validation survey) could not be done in Andhra Pradesh owing to unrest among MFI clients there.

BLP clients were surveyed in all the four regions. This survey was conducted in January and February 2011. All the client interviews were conducted by independent enumerators.

The need for doing extensive validation survey was simple. One, as some of the survey in round 1 were done by the field officers of the MFI concerned, an incentive to "over report" the movements may be present. Therefore, we needed an extensive validation (between 30-40%) of round 1 survey so that, in the event some of the round 1 data was "inadmissible", the replacement data from round 2 would be sufficient to make inferences. It was ensured that for every MFI per cell at least 40 households were surveyed. The round 2 survey was entirely conducted by independent enumerators (mostly students from nearby areas). The validation survey was conducted from the same branches where round 1 survey was done. For the validation survey, a simple random sampling without replacement was done. However, we defined a probability cut off (based on our logit regression) and counted the proportion of individuals in the two sample who had crossed the probability cut off from below. At a group level, the results were largely inconclusive and gave us no indication to replace the original observations. However, certain responses were ignored (irrespective of the rounds in which the survey was done) if data that were crucial for scoring was missing. The estimated movements of those MFIs from round 1 surveys (where their field officers did the survey) and those from round 2 surveys (where independent enumerators did the survey) are given in table 4.11. The entire study is presented with pooling both the data sets.

The questionnaire was designed keeping the scorecard approach in mind. All questionnaires were bilingual (English and the local language). The enumerators were from the same State where they were doing the survey. Although the State Coordinators were explained the objective of the study, the enumerators were not disclosed the objective of the study thereby minimizing the chances of "strategic reporting". A copy of the questionnaire (in English) is given in Appendix A.

APPENDIX F: SCORECARD

F.1 Scorecards

We have used a logit regression procedure for calculating the weights for the household characteristics in our scorecards. This is similar to Schreiner (2008) using a stepwise logit regression to identify the weights to be used in the scorecard.

F.1.1 Methodology

Schreiner (2008) has demonstrated that simple scorecards using information on possession of household articles (as well as some demographic details) can be effective in measuring poverty rates. He uses a single score for all of India. However, we have taken a more granular approach and gone for 28 scorecards (for 14 states, and for rural/urban classification) separately. The rationale for such an exercise was threefold:

1. We ensured that the scorecards are sensitive to the price differentials existing in state-sector combinations.
2. Performance of a predictive model in different geographic regions in a big and diversified country like India can be due to local factors which are diverse in nature.[24]
3. We already had a stratified scheme for our study and that assumed there were at least some regional (along with the sectoral) differences.

As can be seen in the differences in weights of different features included in each scorecard, there exists differential relationship between demand for goods for given income in different regions (sectors) of India.

The only large-scale consumption survey[25] we have in India are the consumption rounds conducted by the National Sample Survey Organisation (NSSO). In particular, we used the NSS consumption rounds of 2004-05 (61st round) to create/calibrate the scorecards.[26] Further, since the survey covers 14 states spread over India, we ensure that the scorecards are sensitive to the price differentials across urban and rural classifications and across different states.

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[24] For example, procuring certain assets may be prevalent culturally in some parts of the country but not in other.

[25] The official consumption poverty measures are based on the NSS consumption rounds.

[26] We had developed a separate scorecard based on Round 55 (1999-2000) to capture clients who joined before 2004. However, in this study we did not use that for reasons mentioned in footnote 7. Indeed, official report published by Planning Commission of India suggests that the poverty estimates obtained from this round is not comparable to the other rounds (http://planningcommission.gov.in/reports/genrep/rep_pov.pdf)

The creation of scorecards went through the following stages:

- Setting state and rural-urban specific consumption thresholds
- Delimiting a set of features (household characteristics) on which the scorecards would be based.
- A recursive algorithm to select the sets of features that are to be included in the scorecards
- Validating the models
- Scaling the regression weights obtained in step 4, above, appropriately so that we arrive at the scorecards
- Calibrating the scaled values obtained in step 5 to likelihoods of being poor

F.1.2 Consumption thresholds

We have used the purchasing power parity PPP measure of $ 1.25 for our consumption threshold from Schreiner (2008).[27] An earlier version of the study had used the mpce cutoff using the current PPP rates for consumption expenditure, obtained from the World Bank[28], were converted to Rupee terms. For the score card based on Round 55, we used the PPP conversion factors from the World Bank documents and corrected for state sector specific prices using appropriate Consumer Price indices.

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F.1.3 Selection of characteristics and the model

NSSO round of 61st was used to arrive at an exhaustive list of characteristics to choose from for the scorecards. For selection of characteristics (we shall use the term features for characteristics), we ensured that the scorecards are as broad based as possible by including ten assets and the primary source of energy used for cooking and lighting covered in the NSS. Another consideration while selecting the features was the use of 'recall' as an instrument in the questionnaires for gauging the consumption levels of clients before they joined the MFIs.

We list below the steps followed in choice of the set of features for the creation of scorecards:

- Our choice of the feature universe was limited to the ones available in Schedule 1.0 of NSS 61st Round, which was used for the collection of data on the consumption round.
- We screened features that are likely to be correlated with the welfare measure we use (consumption levels).

[27] However, it was producing consistently higher poverty rates. Therefore, we decided to adopt the PPP tables as in Schreiner (2008). The PPP table used earlier is given in table 3.3

[28] See http://siteresources.worldbank.org/ICPINT/Resources/icp-final-tables.pdf

- We ruled out features that are time invariant. This was necessary since we use a recall method for estimation of the welfare levels of the clients before they joined the MFIs. Therefore, we did not include demographics like social category, religion, household size, education levels etc.
- The final consideration was that the scorecards needed to be simple to use and hence, we did not include features that pertain to consumption of perishable items. We also did not use complex combination of features.

The questionnaire developed by us gathered information on all these assets.[29]

F.1.4 Feature selection process

Endogenising the weights and the selection of exact characteristics for the scorecards was achieved through a recursive logistic regression procedure and judgement.

The procedure to develop scorecard involved two distinct steps-data preparation and feature selection. The NSS dataset was divided into state-sector (sector here refers to urban/rural status) subsets. We have 14 states included in the survey, giving us 28 sub datasets and the feature selection process was used independently for these 28 datasets.

Every NSS sample was divided into two sets in the ratio ¾ to ¼. The first sample, known as the 'training sample' was used to develop the models and the second served as the validation and the calibration sample. The continuous welfare measure (consumption expenditure) was transformed to a binary variable conditioned on the threshold (deflated $1.25 consumption per capita per day). Thereafter, all the categorical variables were transformed so that each category now becomes a binary variable. However, we also used judgement to select or drop few assets. We developed 29 scorecards in all, 2 each for the 14 states and one for all India. The models were tested for predictive accuracy in a hold out sample. At the end we use 10 state sector specific models and scorecards and 1 all India level score cards.

F.1.5 Validation of the models and calibration of likelihoods

We validated the models in the holdout samples. The criterion adopted was "percentage of correct classification. Of the 28 models for different state-sectors, and the one all India model, 10 state-sector models were chosen. For the rest of the state-sectors, the all India model was earmarked.

[29] See appendix C for the questionnaire.

Once the models are decided on, we perform a simple transformation of the logit coefficients for (the exponentiation of the coefficients or the odds ratios) such that all the maximum score that a household get adds up to 100 to create the scorecards.

The final step in the process is the calibration of the scorecards. For this, we divide the scores (between 0 to 100) into 5 equal sized bins for each scorecard and associate each bin with a likelihood of being below $ 1.25 per capita per day. This calibration was done in the training sample but its bias was calculated over 1000 bootstraps in the holdout sample. We report the table of the biases with the calibrated likelihood for each scorecard in Table 3.2.

Annexure I:

Glossary of terms:

Organizational types:

NBFC (Non-Banking Financial Company) is a company registered under the Companies Act, 1956 of India, engaged in the business of loans and advances, acquisition of shares, stock, bonds, debentures and securities issued by government or local authority, or other securities of a marketable nature, leasing, hire-purchase, insurance business, or chit business: but does not include any institution whose principal business is that includes agriculture or industrial activity; or the sale, purchase or construction of immovable property. NBFCs perform functions similar to that of banks; however there are a few differences in that an NBFC cannot accept demand deposits; an NBFC is not a part of the payment and settlement system and as such, an NBFC cannot issue cheques drawn on itself.

A **Non Profit Organization** can be registered in India as a Society, under the Registrar of Societies or as a Trust, by making a Trust deed. A third option is registration as a section-25 Company under the Companies Act, 1956. Whether a trust, society or section-25 company, the Income Tax Act, 1961 gives all categories equal treatment, in terms of exempting their income and granting 80G certificates, whereby donors to non-profit organizations may claim a rebate against donations made.

Section 25 companies are those companies which are formed for the sole purpose of promoting commerce, art, science, religion, charity or any other useful object and have been granted a license by the central government recognizing them as such. Such companies should intend to apply its profits, if any or other income only in promoting its objects and must also prohibits payment of dividend to its members.

Registered Societies: Societies registration Act, 1860 is a central act for registering not-for-profit organizations. Almost all the states in India have adopted (with modifications) the central Act for creating state level authorities for registering various types of not-for-profit entities.. According to the act any seven persons who subscribe to the Memorandum of Association (MOA) can register a society. The memorandum should include names of the society, its objectives, its names, addresses and occupations of the members subscribing to it as well as the first governing body to be constituted on registration.

Public Trust: Public trust can be created for public charitable purposes. There is no All India Level Act for setting up public charitable trusts. Some of the states in India has enacted the Public Charitable Trust Act, while most states in India does not have a trust act. An NGO can be created only under a public trust act. Madhya Pradesh and Rajasthan have independent state level public trust acts. States like West Bengal and Bihar, do not have any act to register a public trust.

Co-operative Societies: In India, cooperative societies are regarded as instruments to mobilize and aggregate community effort to eliminate layers of middlemen in any product or service supply chain hence resulting in greater benefit sharing for the farmer, worker or artisans. The Cooperative Credit Societies Act, 1904 enabled formation of cooperatives for supplying to farmers cheap credit and protect them from exploitation in the hands of the moneylenders. The cooperative act 1912 expanded the sphere of cooperation and provided for supervision by central organization.

Mutually Aided Co-operative Societies (MACS)

MACs are registered under the Mutually Aided Co-operative Societies Act or Self Financing Co-operative Societies Act in several states. In the societies under the enactments, Government capital is prohibited and the management of the societies is vested in the Board of Directors and the policies are decided by the General Body subject to limited regulatory powers exercised by the Registrar by way of registration of society, registration of bye laws, etc. These State enactments are in addition to the existing State laws on co-operative societies and provides alternative legal framework for co-operative societies. However, in some States (like Orissa), the State enactments provide for creation of a cooperative as distinguished from a co-operative society.

Local Area Banks (LABs): LAB is registered as a public limited company under the Companies Act, 1956. It is licensed under the Banking Regulation Act, 1949. The minimum paid up capital for such a bank shall is Rs 5 crore. The promoters' contribution for such a bank shall at least be Rs 2 crore. The promoters of the bank may comprise individuals, corporate entities, trusts and societies. In the application for a banking licence the details of the initial contribution of promoters, and the manner and method through which the minimum share capital of Rs.5 crore will be raised will need to be indicated. The area of operation of the proposed bank shall be a maximum of three geographically contiguous districts. It is expected that their lending will be to agriculture and allied activities, SSI, agro-industrial activities, trading activities and the non-farm sector with a view to ensuring the provision of timely and adequate credit to the local clientele in the area of operation. The banks will observe the priority sector lending targets at 40% of net bank credit (NBC) as applicable to other domestic banks. Within the above target these banks will adhere to the requirement of lending at least 25% of their priority sector deployments (10% of NBC) to the weaker sections.

Lending types:

A **self-help group** (**SHG**) is a village-based financial intermediary usually composed of between 10-20 local women. Members make small regular savings contributions over a few months until there is enough capital in the group to begin lending. Funds may then be lent back to the members or to others in the village for any purpose. In India, many SHGs are 'linked' to banks for the delivery of microcredit. A Self-Help Group (SHG) is a registered or unregistered group of micro entrepreneurs having homogenous social and economic backgrounds; voluntarily coming together to save regular small sums of money, mutually agreeing to contribute to a common fund and to meet their emergency needs on the basis of mutual help. The group members use collective wisdom and peer pressure to ensure proper end-use of credit and timely repayment.

NABARD's SHG Bank Linkage program

Many self-help groups, especially in India, under NABARD's SHG-bank-linkage program, borrow from banks once they have accumulated a base of their own capital and have established a track record of regular repayments. This model has attracted attention as a possible way of delivery microfinance services to poor populations that have been difficult to reach directly through banks or other institutions. "By aggregating their individual savings into a single deposit, self-help groups minimize the bank's transaction costs and generate an attractive volume of deposits. Through self-help groups the bank can serve small rural depositors while paying them a market rate of interest."

Grameen lending/ Joint liability lending/ Group lending: Pioneered by Mohammed Younus, the Grameen Bank's lending has two distinctive features: villagers are held jointly liable for repayments and are asked to make reports about each other. The members in each group self select themselves with a group size between 2-5 members.

Individual lending: Clients are given loan with individual liability.

Annexure II:

Abbreviations:

MFIs

AROHAN	Arohan Microfinance
Ashajyothi	Ashajyothi Mahilabyudaya Society
Bandhan	Bandhan Microfinance India
BWDA	BWDA Finance Limited
Cashpor	Cashpor Micro Credit
ESAF	Evangelical Social Action Forum Microfinance and Investments (P) Ltd
GBK	Gram Bikash Kendra
GFSL	Grameen Financial Services Limited
Grameen Sahara	Grameen Sahara Financial Ltd
GVMFL	Grama Vidiyal Micro Finance Limited
Indur Intideepam	Indur Intideepam Mutually Aided Thrift and Credit Society
ISHWAR	Ichamati Society For Human welfare and Relation
KBSLAB	Krishna Bhima Samruddhi Local Area Bank Ltd
LBT	Lok Biradari Trust
MGSCS	Manidham Grameen Savings Cum Credit Services
Navachetana	Navchetna Micro Finance
Prayas	PRAYAS
Progress	Relation
PSS	Pragathi Sewa Samiti
RASS	Rashtriya Seva Samiti
Sahara	Sahara Uttarayan Welfare Society
Sahara Manch	Sahara Manch
Sarvodaya	Sarvodaya Nano Finance
Satin	Satin Credit Care Network Limited
SKS	SKS Microfinance
SMSS	Star Micro Fin Service Society
SNF	Sarvodaya Nano Finance
VAMA	VAMA Bal Mahila Vikas Samiti
VFSL	Village Financial Services Private Limited
VGBK	Chandanpiri Vibekanada Gramin Bikash Kendra
VSSU	Vivekananda Shishu Seva Kendra
Yukti	Yukti Sewa Samity

States

AP	Andhra Pradesh
AS	Assam
BI	Bihar
CH	Chattisgarh
JH	Jharkhand
KA	Karnataka
KE	Kerala
MA	Maharasthra
MP	Madhya Pradesh
OR	Orissa
RA	Rajasthan
TN	Tamil Nadu
UP	Uttar Pradesh
WB	West Bengal