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Microfinance and Household Poverty Reduction: Empirical Evidence from Rural Pakistan

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Abstract

This study examines whether household access to microfinance reduces poverty in Pakistan and, if so, how and to what extent. It draws on primary empirical data gathered by interviewing 1,132 households in which both borrower and non-borrower households were interviewed in 2008-9. Sample selection biases have been controlled partially by using propensity score matching. The study reveals that microfinance programmes had a positive impact on the participating households. Poverty-reducing effects were observed on a number of indicators, including expenditure on healthcare, clothing, household income, and on certain dwelling characteristics, such as water supply and quality of roofing and walls.

Keywords: Microfinance; poverty; impact assessment; propensity score matching; Pakistan

JEL Classification: C21, G21, O15

1. Introduction

Poor households in both urban and in particular, rural areas in many developing countries do not have easy access to basic financial services. Their ‘systematic exclusion’ from formal financial services has led to the evolution of an alternative mode of finance, microfinance, where financial services are provided not through traditional routes, such as local money lenders, cooperatives or banks, but through NGOs or microfinance institutions (MFIs). Microfinance has evolved and expanded from Bangladesh to other developing countries over the last three decades. The model is based on the conviction that the livelihoods of such financially-excluded poor households without any physical collateral or credit history can be improved if they are provided access to small-scale loans or other related financial services, such as savings or insurance.

While a few empirical studies at the micro level have shown that participants in microfinance programmes have progressively become capable of accessing financial services and escaping from poverty (Matin et al. 2008, Hossain and Zahra 2008), the wider literature on impact evaluations of large-scale programmes has revealed mixed and conflicting findings, with some disagreements amongst academics and practitioners about the effectiveness of microfinance as a poverty reduction measure. At one end of the spectrum lie the studies that have concluded that microfinance is a positive and effective measure of poverty reduction (e.g. Hossain 1988; Barnes 2001; Dunn 2002; Snodgrass and Sebstad 2002; Goldberg 2005; Khandker 2005; Rabbani et al. 2006; Haseen 2006; Mahjabeen 2008; Banerjee et al. 2009; Imai et al. 2010; Imai and Azam 2012). At the opposite end are studies which have argued that employing this strategy has in fact driven people into greater poverty and has weakened the position of women even further, rather than empowering them (e.g. Goetz and Gupta 1996; Neff 1996; George 2006; Chanana 2007; Bateman 2008). In between, there are studies that have cautioned against considering microfinance as a ‘cure-all’, yet have endorsed it as assisting people to a certain extent, and have urged that it should be used with ‘cautious optimism’ (e.g. Bello 2006; Banerjee, Duflo et al. 2009; Karlan and Zinman 2009; Duvendack and Palmer Jones 2012). Regardless of the different and apparently contradictory conclusions that have been derived from these empirical studies, which might have reflected the diverse settings of the studies (focusing on different geographical areas or drawing on different methodologies), impact assessment nevertheless remains one of the most powerful tools by which programme effectiveness can be measured.

In Pakistan, the microfinance sector has been operational in various forms and sizes for over four decades. Nevertheless, there is a dearth of reliable studies attempting to measure impact using rigorous methods. Claims about the impact of microfinance are not well documented or supported by verifiable evidence (Hussein and Hussein 2003), one of the main reasons for this being the limited availability of primary and secondary data in Pakistan (OPM, 2006).

There are, however, a few empirical studies that have generally confirmed that microfinance intervention has had some positive impacts on the welfare of households in Pakistan. For example, Hussain (2003) shows that there are significant differences between participants and non-participants in microfinance programmes in terms of monthly per capita expenditure, living conditions, literacy rates and, more importantly, increase in income of participants. Montgomery (2005) contends that microcredit programmes have a positive impact on both economic and social indicators of welfare, as well as income-generating activities, especially for the very poorest participants in the programme. Finally, Shirazi and Khan (2009) show that microfinance programmes have a positive impact on poverty reduction in Pakistan and argue that borrowers tend to shift to higher income groups during the given period.

Multi-dimensional aspects of poverty are particularly relevant to Pakistan. The poor in Pakistan not only have low levels of income, they also lack access to basic services such as clean drinking water, adequate sanitation, proper education, financial services, employment opportunities, efficient markets, and sufficient and timely health facilities (World Bank, 2007). Despite considerable efforts through various poverty alleviation programmes, widespread social and economic poverty remains a core problem in Pakistan as its economy is based predominantly on agriculture. Almost 65 percent of the population reside in rural areas and are directly or indirectly linked to agriculture (CIA 2010, World Bank 2002). The FAO (2009) estimates that around 66 percent of the population of Pakistan relies on agriculture for its livelihood. Consequently, the poor are overwhelmingly concentrated in rural areas, where the poverty headcount is 27 percent, more than double the size of that in urban areas. Furthermore, 80 percent of the total poor live in rural areas (IMF 2010). According to the 2007-08 estimates, 22.3 percent of the country's population lives below the poverty line, with another 20.5 percent living in vulnerable conditions (Haq 2008).

The limited access to financial services in the developing world is one of the main obstacles to both income generation and social protection. Nenova et al. (2009) report that nearly 50 percent of Pakistan's population does not engage in either formal or informal financial systems and an estimated 30 percent are involuntarily excluded through lack of understanding and awareness. Despite considerable efforts, microfinance has been slow to scale up, and outreach to women has been particularly limited. It is estimated that only about 8 percent of poor households receive credit from formal sources (World Bank 2007). The size of Pakistan's population and the number of the poor imply that there is a large potential market for microfinance in Pakistan, which, according to PMN estimates, is close to 27 million individuals (Haq 2008), thus bringing the current penetration rate to just 6.97 percent. A study by Ghalib (2013) revealed that the poorest are being significantly underserved by MFIs in rural parts of Pakistan. Given such high levels of poverty and such low levels of service penetration, it is expected that such financial services will increase over the coming years. Therefore, it becomes necessary to rigorously assess the impact that the model produces on livelihoods in the Pakistan setting.

Such studies that empirically assess the impact of microfinance at the household level are few, despite the increasing involvement of MFIs in various poverty reduction programs. The present study aims to address this gap and provide evidence on the relationship between the role of borrowing from MFIs and the ensuing impact on poverty reduction across a number of socio-economic factors.

The study employs a quasi-experimental research design and makes use of cross-sectional data that one of the authors collected in 2008-9 by interviewing 1,132 borrower and non-borrower households across 11 districts in the rural areas of the Punjab province of Pakistan. Household characteristics are captured across four dimensions, further segregated into various indicators, designed to capture various socio-economic characteristics, such as household income and expenditure, household assets and general living conditions, etc. Sample selection biases are controlled partially by matching propensity scores. Findings reveal that despite borrowers seemingly faring better than non-borrowers across around 70 percent of the indicators, a majority of these are not statistically significant. This suggests that despite producing *some* degree of positive impact, MFIs still have to make sustained efforts to bring about real change to improve livelihoods of the poor.

The rest of this paper is organised as follows. The next section summarises the survey design and descriptive statistics. Section 3 describes the econometric methodology and model used to control for sample selection biases. Section 4 discusses the results obtained and the main findings of the study. The concluding remarks are presented in Section 5.

2. Survey design and data

This study aims to assess the nature, extent and direction of the socio-economic impact of microfinance programmes on borrowers, based on detailed cross-sectional primary household surveys conducted over eleven districts across the rural parts of Punjab, in Eastern Pakistan. The study is based on a quasi-experimental design survey[i] whereby comparison is made between two groups of respondents: the control group (represented by non-borrowers) and the treatment group (comprising borrowers). The total sample of 1,132 respondents comprises 463 borrowers and 669 non-borrowers. Our broad research question is whether participation in microfinance programmes improves the socio-economic conditions of member households.

In order to select households, a four-stage random stratified sampling technique was applied. In the first stage, 11 out of the 36 districts were selected from the entire province. Districts were selected systematically as opposed to being selected randomly, in order to control for social and economic disparities that occur across the province between various districts, and to ensure that the selected districts represent maximum and diverse population across the entire province. Starting from the North of the province, districts were selected towards the East, West and South. In the second stage, at least one *tehsil*[ii] was randomly selected from each identified district. In the third stage, at least two villages were subsequently selected randomly from amongst the selected tehsils and in the fourth and final stage; participating and non-participating households were selected at random for conducting surveys.

2.1 Selection and choice of indicators applied

Due to the multidimensional nature of poverty (Armendariz and Morduch 2005; Daley-Harris 2006), it is necessary to have a representative nature of dimensions and accompanying indicators that would reflect the actual poverty of a typical household within the sample frame. After careful screening and extensive pilot testing, the final field instrument comprised questions designed to capture information across the following four dimensions: human resources, dwelling, food security and vulnerability, and ownership of household assets. Table 1 lists the dimensions and related indicators used in the survey.

[Table 1 to be inserted around here]

Out of the four dimensions, assets tend to be most stable over time and hence are a better indicator of economic well-being than income or expenditure. Moreover, assets are normally calculated to represent an annual estimate and represent the enduring results of income flows and expenditures. Another important role that household assets play during 'lean' periods is helping to cope with adverse conditions and in periods of low and unstable income; as their disposal can 'smooth' consumption and expenditure during crises. Household assets in the survey were captured across two dimensions: physical assets (tangible) and human capital (intangible). Tangible assets were further classified into livestock, transport-related assets, savings (financial capital), and appliances and electronics.

The questionnaire was field-tested and a number of indicators were consequently altered to control for local specificities. This measure also ensured that indicators fully captured and reflected relative poverty levels of both groups of households. Indicators such as those relating to highly contextual and subjective responses were subsequently dropped from the final field instrument.

Thus, the indicators, treated as outcomes of interest, in this paper are those reported in table 2. These indicators cover the dimensions of livestock, transport-related assets, savings, appliances and electronics and human development indicators. These indicators capture the overall performance of households who joined the MFI programme in contrast to those who did not.

2.2 Descriptive statistics and explanation of variables

The survey represented eight MFIs in the province. Given the strong nationwide presence of the National Rural Support Programme (NRSP), its borrowers represented almost 32 percent of the total sample. The Kashf Foundation’s strong presence and extensive outreach in the districts surrounding the provincial capital gave it a share of 28 percent, and the Punjab Rural Support Programme (PRSP) was represented by 14 percent of those interviewed. In terms of the number of loan cycles that respondents had completed at the time of interview, almost 60 percent were found to be within their first two years of borrowing, while 16 percent were in their third cycle. By principal occupation, although the largest group of respondents were involved in casual labour, at over 32 percent, there is a significant disparity when data is disaggregated across borrowers and non-borrowers. That is, 22 percent of borrowing households reported their occupation as casual labour, as opposed to almost 40 percent of non-borrowing households.

For social and cultural reasons, extended families are common in Pakistan, particularly in the rural areas. The most commonly-occurring size of households (mode) was five members. The mean size calculated from the data was 5.98 members per household and the median value 6.00. Household sizes of five to seven members constituted almost 50 percent of the entire sample, while those consisting of eight or more members amounted to around one quarter, and single to four-member households accounted for the remaining 25 percent of the sample. The national average household size is 6.58 members, according to the Household Integrated Economic Survey (GoP 2009a), while the average for Punjab was reported as 6.33 members for 2007-08, close to the mean (5.98) and median (6.00) values reported in the survey results.

In terms of loan size, 22 percent of respondents had availed themselves of loans ranging from Rs. 5,000 to Rs. 10,000, and 30 percent had credit facilities ranging from Rs. 11,000 to Rs. 15,000. Taken together, these loans (up to Rs.15,000) constituted more than half of the sample. Instalment amounts also corresponded proportionately to the size of loans; it was noted that over 60 percent of the instalment amounts varied from Rs.1,000 to Rs.2,000 followed by smaller amounts of up to Rs.1,000, and larger amounts that ranged from Rs.2,000 to Rs.2,500, accounting for almost a quarter of the total sample. The sample mean is Rs.17,473, and the median value Rs.15,000.

Literacy rate, according to the Pakistan Social & Living Standards Measurement Survey (PSLM) for 2007-08 (for both males and females, aged 10 and above) was 56 percent at the national level and 53 percent for rural Punjab (GoP 2009b, p. 43). Data from this survey found the adult literacy rate (household members aged 15 and above) to be 39.92 percent, whereas it was 40.02 percent according to PSLM (2007-08). UNESCO's Asia-Pacific Literacy Data Base (2009) estimates Pakistan's adult literacy rate at 54.9 percent (2007 figures estimated in 2008). Both groups of respondents exhibited a fairly uniform pattern, with the borrowing households being slightly better-off in having more literate adults.

PSLM (GoP 2009b) captures data across a series of indicators divided into rural and urban categories across all four provinces, but comparison will only be made with rural Punjab, the province of this study. According to the PSLM survey, 18 percent of the total households in rural parts of Punjab have access to piped water, 44 percent use hand pumps and 35 percent have motorised pumps in their homes. These figures were close to those obtained by the survey carried out for this study, in which 53 percent reported using hand pumps and 30 percent had motorised pumps. Data published by PSLM for access to toilet facilities revealed that 51 percent had access to flushed toilet systems and 49 percent did not have any facility at all. The survey for this study found 57 percent and 42 percent for the two classes respectively. Data for drainage systems were captured across three categories: covered, open and no facility, which was reported by the survey at 6 percent, 67 percent and 27 percent respectively.

In addition to water and sanitation facilities, the survey for this study captured vital data relating to households' general dwelling conditions. Data collected for home ownership showed that around 94 percent of respondents owned the houses they were living in. Roofing structures were dominated by metal beams and bricks at 52 percent, followed by wooden beams and bricks at 42 percent. Only 6 percent of the houses had concrete roofs. For construction of exterior walls, bricks were used in 75 percent of the cases, and mud for the remaining 25 percent. Mud was more commonly used as flooring material (68 percent) as opposed to the brick or cement floors found in the remaining 32 percent of houses. Electricity for lighting was reported at over 95 percent. In terms of type of energy used for cooking, the most common form was firewood (65 percent), followed by 27 percent that used animal-dung cakes (the cheapest alternative); only 8 percent used methane gas cylinders.

Finally, the field instrument contained questions that were designed to capture elements of borrowers' behaviour, views and attitudes towards credit. In terms of purpose of obtaining credit, 43 percent stated that it was for establishing a new business, while 57 percent reported its use for expanding businesses. When asked about the usefulness of the loan, around 81 percent expressed satisfaction, but 19 percent reported not finding it beneficial. This figure of unsatisfied borrowers matches the proportion of those who had no plans for borrowing in future (17 percent); around 75 percent were willing to borrow in the next cycle and around 8 percent were still undecided at the time of interview. As expected, delinquency was almost absent and the repayment rate was very high (approximately 99 percent), an indication that borrowers continue to repay regularly, despite the difficulties that they face or their decision not to borrow in future. What is noteworthy, however, is that 'missed' payments were usually paid in the following month, and hence cannot be considered 'defaults' per se.

3. Modelling methodology

We measure the impact of treatment on the outcome, which is the impact of borrowing within MFI programmes on the livelihood of the households, by estimating the difference between individuals who received the treatment and those who did not receive the treatment. We apply the standard approach of matching widely used in the literature, formalised by Rubin (1973).

First, this difference can be defined as:

$$\Delta_i = Y_i^1 - Y_i^0 \qquad (1)$$

where Δ_i is the treatment effect of individual *i,* in which $i=1,2,\dots,N$. Y_i^1 and Y_i^0 are the potential outcomes for treated and non-treated individuals respectively. Even though we use cross-sectional data (as opposed to panel data) equation (1) is supposed to approximate the difference between the potential outcomes before and after receiving the treatment for each individual under certain assumptions. It is noted that, for each individual *i* in (1), there is only one observed outcome and the other is counterfactual and is not observed from the data. This makes it impossible to directly calculate, using cross-sectional data, the difference between the outcomes before and after treatment for each individual or household.

Therefore, equation (1) is modified to estimate the average treatment effects on the treated, Δ_{TT}, which can be expressed formally as:

$$\Delta_{TT} = E(\Delta \mid D=1) = E(Y^1 \mid D=1) - E(Y^0 \mid D=1) \tag{2}$$

Δ_{TT} measures the difference between the expected outcome with and without treatment for the actual participants. The term $E(Y^1 \mid D=1)$ represents expected outcomes for programme participants, while $E(Y^0 \mid D=1)$ is the hypothetical outcome that would have resulted if the programme participants had *not* participated. In short, equation (2) allows extraction of the effect of the treatment programme on the treated from the total effects estimated. Finally, equation (2) is used in the present study as an estimator to answer this counterfactual question: 'What would be the state of those individuals who participated in microfinance programmes if they had not actually borrowed?'

3.1 Selection bias issue

Equation (2) suffers from the problem of unobservability. That is, we can estimate $E(Y^1 \mid D=1)$, while the term $E(Y^0 \mid D=1)$ cannot be estimated since it is not observed. An alternative way to estimate Δ_{TT} is to use the mean outcome of untreated, $E(Y^0 \mid D=0)$, as an approximation for $E(Y^0 \mid D=1)$. If the approximation $E(Y^0 \mid D=1) = E(Y^0 \mid D=0)$ holds true, then non-participants can be conveniently used as the comparison group. However, with non-experimental data, this condition does not generally hold, since the components which determine the participation decision also determine the outcome variable of interest. Consequently, the outcomes of participants would be different even in the absence of programme participation giving a raise to selection bias problem.. This implies that equation (2) is described as:

$$E\left(Y^1 \mid D=1\right)-E\left(Y^0 \mid D=0\right)=\Delta_{TT}-\left[E\left(Y^0 \mid D=0\right)-E\left(Y^0 \mid D=1\right)\right] \quad (3)$$

where the term $E\left(Y^0 \mid D=1\right)-E\left(Y^0 \mid D=0\right)$ measures the size of the bias due to unobservables. Thus, the 'true' value of the average treatment of the treated, Δ_{TT}, can be identified when the bias is zero, or:

$$E\left(Y^0 \mid D=1\right)=E\left(Y^0 \mid D=0\right) \quad (4)$$

When the bias is due to observables, we face a scenario known as *self-selection bias.* This refers to the case that the outcomes are not observed for all individuals since they cannot participate in the treatment programmes at the same time.

There are a number of approaches to handle this bias that can be found in the literature. One approach to handle this bias is by implementing matching procedures, such as covariate matching (as in Rubin 1973) and propensity scores as suggested by Rosenbaum and Rubin (1985) (RB, hereafter), which use non-participants' available information to estimate the impact. In this context, the Propensity Score Matching (PSM) approach proposed by RB helps reducing the dimensionality problem, which arises from the application of covariate matching.

An alternative approach to control for the bias due to unobservables is the application of instrumental variables (IV) approach, as in Heckman (1997) and Moffitt (1996). One of the methodological advantages in using statistical matching rather than the IV estimation approach is that the former does not assume linearity and is valid even though distributions of explanatory variables of treatment and control groups overlap relatively little; and it does not require a valid set of instruments[iii]. However, the matching approach (e.g. PSM) does help to eliminate much of any bias associated with unobservables. Indeed, replication studies comparing non-experimental evaluations, such as PSM, with experiments for the same programs do not appear to have found such an example in practice. For example, Heckman et al. (1998) in an evaluation of job training programmes have shown that the matching method applied to the control groups in the same labour markets using the same questionnaire would eliminate much of the selection bias associated with unobservables, although the remaining bias is still non-negligible. Furthermore, Chemin (2008) applied PSM to the cross-sectional household data set on Bangladesh in 1991/2 and evaluated the impact of participation in microfinance programmes on a number of outcome indicators. The study found that microfinance had a positive impact on participants' expenditure, supply of labour and male/female school enrolment. The results are consistent with an earlier study by Pitt and Khandker (1998) who applied the IV technique to the same data. In our data, the members of the control group were selected to be geographically close to the members of the treatment group, and the same questionnaire was used for both groups, so it is conjectured that selection bias on unobservables has been minimised. Thus, in the context of this study, we apply PSM to correct for the bias.

3.2 Assumptions:

The assumption to counterfactual unobserved outcome of stable unit treatment value is assumed to hold in the context of this paper (see Rubin (1980)). This assumption implies that individuals' potential outcomes depend on individual's own participation and not on the treatment status of other individuals in the population. The importance of this assumption is in that it rules out the possibility of peer and general equilibrium effect.

In addition to the above assumption, two broad assumptions are imposed at this stage to estimate the treatment effect that is selection bias free. The first is exogeneity of the treatment, known as *unconfoundedness*, and the second is the *overlap* condition.

The assumption of unconfoundedness implies that differences in outcomes – before and after treatment outcomes- are only due to the implementation of the treatment programme. Moreover, the set of covariates, X, is not affected by the treatment and assumed to be all captured in the model (i.e. no omitted variables). The assumption formally is defined as:

Assumption 1.A: $Y^0, Y^1 \perp D \mid X$ (5A)

where '$\perp$' is the symbol for independence.

The second requirement is to ensure all individuals with the same characteristics in the sample (e.g. the same covariates) have positive probability of being participant and non-participants. In order to achieve this condition, one need to define the following overlap condition:

Assumption 2.A: $0 < P(D = 1 | X) < 1$ (6A)

The overlap condition rules out the perfect predictability of participation conditional on the characteristics identified by the set of covariates *X*. (i.e.) and the effects of treatment on the treated,

These two assumptions combined allow us to estimate the effect of treatment on the treated, Δ_{TT}. The two assumptions, as argued by Imbens (2004), can be relaxed when estimating Δ_{TT} to their weaker versions[1]:

Assumption 1B: $Y^0 \perp D | X$ (5B)

Assumption 2B: $P(D = 1 | X) < 1$ (6B)

The weaker version of unconfoundedness assumption in (5B) requires the independence of only the outcome for the controls; while the weaker overlap condition in (6B) requires that all conditional probabilities are strictly less than 1.

3.3 PSM Estimator and estimation methodology

Equation (2) is estimated from the PSM estimator. RB introduce what is known as a balancing score to avoid the problem of high dimensionality. The balancing score suggested by RB is defined as a propensity score, which is a function that estimates the probability of participating in the programme given the observed covariates (e.g. observed characteristics for each individual). Formally, the propensity score is defined as:

$$P(D = 1 | X) = P(X) \tag{8}$$

This latter is estimated using one of the models available in the literature, such as the logit or probit model. These models predict the likelihood that individuals would join the microfinance programmes conditional on their personal characteristics. Following much of the literature, equation (8) is specified as a probit model and expressed as follows:

$$P(D=1 \mid X) = P(y^* > 0 \mid X) = P(u > -X\beta \mid X) = 1 - G(-X\beta) = G(X\beta) \qquad (9)$$

where $0 < G(X\beta) < 1$, for all values of covariates X, $X\beta = \sum_{j=1}^{k} \beta_j X_j$ and G is a standard normal cumulative function. The model in (9) is non-linear and therefore the estimator implemented is a maximum likelihood estimator.

Equation (9) satisfies the unconfoundness assumption, which implies in this case that potential outcomes are independent treatment, given the set of covariates X such that: $Y^0, Y^1 \perp D \mid P(X)$, as well as the overlap condition. This latter ensures all individuals with the same characteristics in the sample have a positive probability of being participants and non-participants (i.e. $0 < P(D=1 \mid X) < 1$). Therefore, the PSM estimator of Δ_{TT} is selection-bias free. Formally, the PSM estimator defined is as:

$$\Delta_{TT}^{PSM} = E_{P(X)|D=1}\left[E(Y^1 \mid D=1, P(X)) - E(Y^0 \mid D=1, P(0))\right] \qquad (10)$$

A number of matching algorithms have been suggested in the literature to contrast the outcome of treated individuals with the outcome of individuals in the comparison group (i.e. borrowers and non-borrowers). We report the results of two matching algorithms, namely, *stratification* and *kernel* matching[iv], which are widely used in the literature. Using two matching algorithms avoids any shortcomings that may result from relying on a single method, and it also helps to check the robustness of the estimated impact.

3.4 PSM Estimates: general discussion

Appendix 1 reports the estimation output of the propensity score using the probit model reported in the first panel, along with its estimated marginal effects reported in the second panel. The dependent variable is whether the household participated in the microfinance programme. We assume that household composition and characteristics, conditions of housing, infrastructure, and participation in the labour market would affect the decision to participate, and we use the reduced form of equation for the programme participation equation. The explanatory variables include age of household adults, occupation of household head and adults, child dependency ratio, access to electricity, home ownership status (owned or rented), consumption of luxury food, such as beef, percentage of literate adults, and availability and type of toilet.

Among the explanatory variables, electricity supply in house, home ownership, consumption of luxury food (beef), number of rooms in house, consumption of staple food and stock of wheat held had a negative and statistically significant effect on the likelihood of borrowing money, or of joining the programme. This implies that better living conditions as well as higher consumption of beef and staple food lowered the probability of individuals joining the programme. On the other hand, indicators such as child dependency ratio, instances of child labour and availability and type of toilet have a positive and statistically significant effect on the probability of borrowing or joining the programme; these indicators reflect the fact that household members are in deprivation, encouraging one of the members to borrow to set up small family-run businesses.

Distribution of the estimated propensity score of all the households resulted in some 7 observations being dropped from the matching procedure since they lay outside the overlap region. This is shown in Appendix 2 where the propensity score distributions for both groups are displayed. Six blocks are estimated to be within the common support region in which the balancing property is confirmed for each block and all individuals within the range [0.11, 0.982] are kept in the model. Thus 463 borrowers are to be matched to 662 non-borrowers. The intervals identified are of [0.11, 0.2], [0.2, 0.3], [0.3, 0.4], [0.4, 0.6], [0.6, 0.8], and [0.8, 0.982] with 65, 217, 254, 495, 83, 11overlaps in each block respectively. This gives the fourth block the largest overlap, while the last interval has the least number of individuals with common characteristics. In all blocks, the balancing property is tested and there is no significant difference between the means of treated group and control group at 5% level of significance as reported. With the balancing property satisfied and six blocks estimated, the PSM estimator satisfies the unconfoundedness and overlap conditions, and is thus bias free.

Finally, the matching of covariates is well balanced using the propensity score estimated within the common support region. Appendix 3-A reports covariate imbalance tests (the t test) of the equality of the two samples before and after matching. For each covariate we run this test, in which the null hypothesis states that the mean of a covariate in the comparison and treated group are equal. If we accept the null then the two groups are well balanced. The output reported in appendix 3-A indicates that all covariates are well balanced after matching and thus matching quality for each covariate individually is not an issue. This is confirmed by looking at the overall matching quality and comparing the pseudo R^2 of the propensity score model before and after matching. Appendix 3-B shows that the pseudo R^2 falls after matching compared to that before matching, which we expect if the data is well balanced across the two groups. Moreover, the model is jointly insignificant after matching as indicated by the LR statistic since we accept the null with p value equal to 0.82 and the model jointly significant before matching since we accept the alternative hypothesis having an LR statistic with p value equal to zero. In addition, matching reduce the bias by a significant magnitude from 13.8 before matching to 3.9 after matching.

4. Survey findings: economic and social impact of microfinance

The sections above discussed the methods and various procedures adopted to control the sample of any selection biases. Once tests showed that both groups (control and treatment) were at par, the average treatment-on-treated effect (ATT) and the t-statistics for each indicator across the four dimensions of well-being were calculated, as shown in Table 2. As discussed in detail below across each dimension, statistically significant values provide strong evidence that disparities in both groups did not occur merely by chance, but are attributable to programme participation.

[Table 2 to be inserted around here]

4.1 Asset accumulation and household well-being

For the rural poor, livestock constitute an important category of assets, as they can be classified as 'income-generating' and provide a means of livelihood. A substantial portion of borrowing was done to purchase cows and goats, and some households relied exclusively on livestock as a source of income, although they were found to provide supplementary income in most cases. Survey findings show that borrowers seem to fare better in terms of livestock-related assets, albeit not to a significant level. Differences in poultry, being of small monetary value, show borrowers to be marginally at an advantage (on the average between both methods) by around Rs.170; they were statistically non-significant with t statistics 1.50. ATT for cows was positive and large, but not statistically significant and do not lead to any firm conclusion.

In the case of transport-related assets, non-borrowers seemed to fare better, although the differences were not statistically significant. Bicycles were the only asset where borrowers seemed to be better off, by small amounts, as compared to non-borrowers, by values ranging from Rs.136 to Rs.142 across the two methods used for comparison, with *t* statistics ranging from 1.51 to 1.62.

Savings constitute an important component of financial capital. Robinson (2001, p.21) argues that 'deposit services are more valuable than credit for poorer households. With savings, not only can households build up assets to use as collateral, but they can also better smooth seasonal consumption needs, finance major expenditures such as school fees, self-insure against major shocks, and self-finance investments'. Owing to the variation in policies and the erratic and inconsistent saving behaviour of client households, the most suitable and relevant proxy for establishing saving behaviour of respondents was considering participation in ROSCA (Rotating Savings and Credit Association) schemes, which are a form of informal saving model found in many parts of the world, known by different names. Survey findings show that there is a marked difference in saving behaviour across both groups. As shown in Table 2, borrowers show a much higher probability and incidence of participation in ROSCA schemes than did non-borrowers. Moreover, there was an average difference (ranging from Rs.1,723 to Rs.1,545, across kernel and stratification methods) in the encashment amount of the scheme, with borrowers saving greater amounts and, as would be expected, contributing more (around Rs.105 monthly) towards instalments. A possible explanation is that once rural households start to participate in microcredit programmes they develop a sense of financial access and realise the importance of participating in saving schemes. In the absence of formal options, they resort to semi-formal models (such as ROSCA, in this case) and commit a certain amount to be contributed.

As opposed to livestock, the impact of borrowing on appliances and electronics was not so pronounced. There was a very small, almost negligible difference across household electronics such as fridges, VCRs and sewing machines, whereas non-borrowers seemed to fare slightly better in terms of owning radios. Borrowers, however, seemed to be better off in owning televisions (with average difference in values ranging from Rs.344 to Rs.364 across both methods) as compared to non-borrowers. Borrowers were also found to be better off if comparisons were made of the overall value of appliances and electronics, although the difference was not statistically significant. The overall value of total or per capita household tangible assets owned by borrowers was found to be greater than that of non- borrowers, but it is not statistically significant.

4.2 Human resources

Our survey questionnaire also captures various demographic characteristics of household members, household income and amount spent on clothing and footwear, children's schooling, and healthcare. Clothing and footwear expenditure shows that borrower households spend more than non-borrowers, and the difference ranges from Rs.569 to Rs.632 which is statistically significant at the 5% level. Calculations also reveal that borrowing households' spending on healthcare was on average Rs.148 more than non-borrowers' and the difference is statistically significant at the 1% level. There was a small and non-significant difference in the amount of average monthly schooling expenditure with borrower households spending more.

4.3 Household income and expenditure

Table 2 portrays the differences between both groups of respondents in terms of monthly household income and expenditure. Although overall monthly household expenditure is not statistically significant, monthly expenditure on healthcare is strongly significant (varying from Rs.150 to Rs.153 across matching methods). It was also noted that the difference in expenditure is inconsequential (varying from Rs.220 to Rs.239 across matching methods), whereas the difference in income is both substantial (given that the sample's median income is Rs.7,500), as well as statistically significant at the 1% level. Depending on the matching method used, monthly income of borrowers is greater by Rs.1,300 (stratification) and Rs.1,302 (kernel method). This disparity can be attributed to a number of factors. One possible explanation is that borrowers supplement their income by obtaining microcredit and investing the amount in livestock or other small income-generating assets, such as a sewing machine, bicycle or cart. On the other hand, if they have access to savings, borrowers can combine credit from the MFI and invest in a larger asset, which acts as the primary source of income. Examples from the survey include setting up a roadside hotel, a barber's shop, a bicycle repair shop, buying a donkey-cart, purchasing a cow or selling an existing one and 'upgrading' to a better breed.

4.4 Dwelling-related indicators

The dimension that measured housing conditions was captured across various indicators, such as the type of cooking fuel used, energy used for lighting, material used for constructing floors, roofs, walls, source of water supply, and the method used for waste water disposal. Finally, the overall condition of the house was ranked during interviews by observing its condition. The results show that borrowers seem to live in better conditions than non-borrowers across all indicators except for the type of cooking fuel used and the method of disposing of waste water, where non-borrowers show very slight, negligible instances of being at an advantage. The most pronounced and statistically significant differences were found in 'the type and material used for constructing roofs, internal and external walls' and 'the source of water supply in the house'. All of these reflect better dwelling conditions enjoyed by borrowers.

5. Concluding remarks

Drawing upon a primary provincial-level cross-sectional household survey conducted in Pakistan, the present study analyses the extent and direction of programme impact on borrowers. This was assessed through a range of dimensions which captured and reflected relative well-being of a typical rural household in Pakistan. Household characteristics were captured across four dimensions, further segregated into various indicators, the data on which was gathered by administering a semi-structured questionnaire in the field. The research was based on the quasi-experimental design that compared differences between borrowers and non-borrowers. In order to control for any selection bias that may have arisen during sampling of households, the propensity score matching model was applied, through which the average treatment-on-treated effect was finally computed.

As discussed in the previous sections, borrowers were seen to fare better in most of the indicators across various dimensions of relative household well-being. The extent of the difference across both groups was substantial as well as statistically significant in some indicators, while it was found to be weak and negligible in others. For example, borrowers performed better in terms of livestock, participation in savings schemes, and overall value of household assets. Borrowers' household income and expenditure was also seen to be better and in terms of food consumption they had a slight edge over non-borrowers as they were found to consume more 'luxury' foods and also had larger stocks of storable staple foods. In the case of dwelling-related indicators, borrowers had a better quality of floors, roofs, walls, and water supply in their houses, although non-borrowers seemed to use better quality cooking fuel and had improved waste water disposal systems. The most prominent and statistically significant differences across both groups favoured borrowers, and were observed in savings, televisions, expenditure on healthcare, monthly household income, expenditure on clothing and footwear, and certain dwelling characteristics, such as water supply and quality of roofing and walls. Overall, borrowers were seen to be better in around 70 percent of the indicators across which comparisons were made in the final model. Borrowing households, in comparison with non-borrowers, were therefore able to increase household income by investing more in productive assets, such as livestock or sewing machines; this income was either saved for future investment or was consumed in the form of 'luxury' foods or for stocking staple food items, or was incurred on healthcare. Given the persistence of poverty and vulnerability in rural Pakistan, the results show that microfinance can be used as an effective measure in alleviating poverty in the country.

Despite the limitations in the methodology of PSM applied to cross-sectional data, such as the possible bias arising from unobservable factors, the study reveals that borrowing produced positive effects across a number of socio-economic dimensions, albeit to a limited extent. Poverty reducing-effects were observed and were found to be statistically significant on a number of indicators, such as expenditure on healthcare and clothing, monthly household income, and certain dwelling characteristics, such as water supply and quality of roofing and walls. Across certain aspects such as livestock, total ROSCA encashment amount, value of assets and certain appliances and electronics and human development indicators impact was found to be positive but not statistically significant. This leads us to infer that continued sustained efforts, would make the positive impact even more pronounced, given the limited access to financial services in Pakistan, the low penetration and the potential of MFIs to expand outreach. MFIs in the country can achieve deeper outreach and greater impact by diversifying the product mix and tailoring products to suit seasonal needs. Flexible repayment terms can also be beneficial to the rural poor, as it can suit their seasonal and variable income streams.

The present study assesses how borrowing from microfinance institutions impacts the various dimensions of livelihoods across parts of rural Punjab in Pakistan. The study could be extended across the other three provinces. Moreover, a comparison of all four provinces could assist in evaluating how and what sort of impact development-related funds are producing on livelihoods. Furthermore, such studies at the national scale can lead towards a better distribution of development funds.

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Table 1: List of dimensions and related indicators used in survey

Human resources	Dwelling-related indicators	Food security and vulnerability	Ownership of household assets
Age and sex of adults in household Adult literacy Number of children Occupations of adults in household Number of children below the age of 15 in household Annual expenditure on clothing and footwear for all members in household	House ownership Type of floor Material used for constructing exterior walls and roof Number of rooms in the house Source of water supply Type of toilet. Method of bathroom waste disposal Energy for lighting in the house Type of fuel used for cooking Structural condition of house	Number of days when staple foods were served Number of days when vegetables were served Number of days when meat was served	Livestock (cattle and buffalo, sheep and goats, poultry, horses and donkeys, etc.) Transportation-related assets (motorcycle, bicycle, carts) Appliances and electronics (television, VCR, refrigerator, washing machine, radio/tape/stereo, mobile phone, sewing machine, etc.)

Note: Both income and expenditure were captured at the household level on a monthly basis. To facilitate ease of recall, the period was kept at the monthly level. For income, respondents were asked to give total income from all sources that the household used for making a living. In case of multiple sources, interviewees were encouraged to give a breakdown from all sources. This facilitated them in making calculations and also helped in arriving at the most accurate figures rather than making random guesses. Likewise, monthly household expenditure was also added up as they would go through the various types of expenditures they incurred in a typical month.

Table 2: Average Treatment-on-Treated effect (ATT) and t-statistics across various dimensions and associated indicators

Variables	KERNEL		STRATIFICATION	
	ATT	***S.E.***	***ATT***	***S.E.***
LIVESTOCK				
Poultry	169.290	104.322	174.258	121.757
Cows	4,525.100	4,532.562	4,255.300	5,294.953
Total livestock value	5,665.367	4,808.349	5,328.299	5,163.413
TRANSPORT-RELATED ASSETS				
Motorcycle	-846.157	1,118.940	-823.210	996.614
Bicycle	137.090	90.074	153.000*	83.148
Carts	-271.837	1,351.592	-62.247	1,075.545
Total transport assets value	-980.905	1,747.237	-732.457	1,386.910
SAVINGS				
ROSCA (participation in schemes)	0.080***	0.020	0.077***	0.021
Total ROSCA Encashment Amount	1,675.882	1,481.425	1,711.212	1,277.883
APPLIANCES AND ELECTRONICS				
Mobile phones	-108.687	133.806	-111.774	134.404
Radio	-87.670	54.052	-83.820	53.863
Sewing Machine	32.840	90.862	21.869	83.368
TV	333.491	207.724	277.762	206.115
VCR	-10.450	64.737	-14.666	72.047
Washing Machine	-85.733	157.823	-87.321	150.746
Total appliances and electronics	86.332	670.348	-19.079	734.958
Value of assets per person	622.385	1,065.793	452.492	1,010.307
Total value of household assets	4,770.794	5,652.850	4,576.764	4,806.106
HUMAN DEVELOPMENT INDICATORS				
Per capita expenditure on clothing and footwear	109.157**	49.988	102.660**	44.662
Clothing and footwear expenses per annum	592.458**	252.431	578.518**	292.586

Variables	KERNEL		STRATIFICATION	
	ATT	***S.E.***	***ATT***	***S.E.***
HUMAN DEVELOPMENT INDICATORS (continued)				
Clothing expenditure: percentage of income	-0.181	0.260	-0.213	0.233
Clothing expenditure: percentage of expenditure	0.465	0.348	0.399	0.325
Monthly expenditure on healthcare	153.263***	37.834	149.656***	42.021
Children currently at school	-0.013	0.106	-0.029	0.121
Monthly children's schooling expenditure	29.967	107.493	20.931	128.137
Monthly household expenditure	220.480	239.090	242.960	241.347
Monthly household income	1,302.202***	387.241	1,300.359***	439.474
DWELLING-RELATED INDICATORS				
Type of cooking fuel used	0.084	0.064	0.099	0.076
Material used for constructing floors	-0.034	0.047	-0.039	0.045
Overall condition of house	0.037	0.042	0.024	0.048
Material used for constructing roof	-0.144**	0.060	-0.140**	0.066
Material used for constructing walls	-0.128**	0.055	-0.127**	0.053
Source of water supply in house	0.252***	0.084	0.234**	0.095
Method used for waste water disposal	0.035	0.036	0.044	0.033

Source: Survey data

1% *t* critical value is 2.576 (***significant at 1%).

5% *t* critical value is 1.96 (** significant at 5%).

10% *t* critical value is 1.645 (*significant at 10%)

S.E.: Standard errors.

Appendix 1: Probit estimated score (Dependent variable: whether a household participated in the microfinance programme)

Variables	Probit Estimates	Marginal Effects
Intercept	1.199 (0.762)	-0.013
Value of agricultural land	-0.033 (0.108)	0.002
Average age of household adults	0.004 (0.005)	0.280
Type of occupation 1	0.718** (0.343)	0.145
Type of occupation 2	0.370 (0.337)	-0.030
Type of occupation 3	-0.079 (0.340)	0.109
Type of occupation 4	0.277 (0.344)	0.151
Type of occupation 5	0.381 (0.456)	0.039
Child dependency ratio	0.100** (0.046)	0.097
Child labour	0.252*** (0.091)	-0.120
Electricity supply in house	-0.310* (0.184)	4.99e-6
Value of goats/sheep	1.29e-5*** (4.88e-6)	-0.174
Home ownership status (owned or rented)	-0.449** (0.175)	-0.093
Consumption of luxury food: beef	-0.240** (0.109)	0.001
Percentage of literate adults	0.002 (0.001)	-0.017
Number of rooms in house	-0.044 (0.036)	-0.076
Consumption of staple food	-0.198*** (0.076)	0.061
Availability and type of toilet	0.159* (0.081)	-0.002
Stock of wheat held	-0.005** (0.002)	-0.013

Values in () are standard deviation. Sample size is 1132. The log likelihood ration of the probit model is *LR= 103.59* [p-value=0.00]. $R^2 = 0.07$. ***, ** and * refer to significance at 1%, 5% and 10% level of significance. The model is estimated using STATA's 'probit' function.

Appendix 2: Balancing property test by block

Block 1: $0.11 \le Score_{\Pr obit} < 0.2$				
	Obs	Mean	Std.Err	Income
Non-Borrowers	53	0.162	0.003	7433.96
Borrowers	12	0.160	0.007	6958.33
Combined	65	0.162	0.002	7346.15
Difference		0.007	0.008	475.63
Test (p-value)		0.72		
Block 2: $0.2 \le Score_{\Pr obit} < 0.3$				
	Obs	Mean	Std.Err	
Non-Borrowers	172	0.256	0.028	7575.58
Borrowers	45	0.257	0.029	7388.89
Combined	217	0.256	0.003	7536.87
Difference		-0.001	0.001	186.69
Test (p-value)		0.78		
Block 3: $0.3 \le Score_{\Pr obit} < 0.4$				
	Obs	Mean	Std.Err	
Non-Borrowers	156	0.347	0.002	8840.37
Borrowers	98	0.354	0.003	9188.78
Combined	254	0.350	0.002	8974.8
Difference		-0.007	0.004	-348.79
Test (p-value)		0.07		
Block 4: $0.4 \le Score_{\Pr obit} < 0.6$				
	Obs	Mean	Std.Err	
Non-Borrowers	249	0.484	0.003	8977.51
Borrowers	246	0.493	0.003	10831.3
Combined	495	0.490	0.002	9898.79
Difference		-0.009	0.005	-1853.85
Test (p-value)		0.06		
Block 5: $0.6 \le Score_{\Pr obit} < 0.8$				
	Obs	Mean	Std.Err	
Non-Borrowers	29	0.654	0.01	9500
Borrowers	54	0.674	0.007	10851.85
Combined	83	0.667	0.006	10379.52
Difference		-0.02	0.012	-1351.85
Test (p-value)		0.11		
Block 6: $0.8 \le Score_{\Pr obit} < 0.982$				
	Obs	Mean	Std.Err	
Non-Borrowers	3	0.845	0.008	9000
Borrowers	8	0.887	0.022	15625
Combined	11	0.875	0.017	13818.18
Difference		-0.04	0.038	-6625
Test (p-value)		0.30		

Test: tests the null hypothesis of no difference between borrowers and non-borrowers against the alternative of there is a difference. All computations are performed using STATA's function 'pscore' developed by Becker and Ichino

(2002). The default number of blocks is 5, which is - generally- enough to remove the bias as argued by Cochran (1968) and Imbens (2004). If the balancing property is not satisfied ‘pscore’ re-do the computation with one extra block at a time until the balancing is satisfied. In our case, the estimated number of blocks is 6.

Appendix 3-A: Covariates imbalance testing

Variable	Sample	Mean		t stat	p vlaue
		Treated	Control		
Value of agricultural land	Unmatched	0.294	0.236	2.17	0.03**
	Matched	0.290	0.277	0.44	0.66
Average age of household adults	Unmatched	34.834	34.601	0.47	0.64
	Matched	34.734	34.948	-0.40	0.69
Type of occupation 1	Unmatched	0.289	0.166	5.01	0.00*
	Matched	0.286	0.238	1.65	0.10
Type of occupation 2	Unmatched	0.320	0.262	2.13	0.03**
	Matched	0.321	0.345	-0.77	0.44
Type of occupation 3	Unmatched	0.220	0.392	-6.16	0.00*
	Matched	0.221	0.223	-0.08	0.94
Type of occupation 4	Unmatched	0.145	0.148	-0.15	0.88
	Matched	0.146	0.164	-0.73	0.47
Type of occupation 5	Unmatched	0.015	0.013	0.23	0.82
	Matched	0.015	0.020	-0.50	0.61
Child dependency ratio	Unmatched	1.081	0.947	2.53	0.01*
	Matched	1.065	1.014	0.87	0.38
Child labour	Unmatched	0.151	0.085	2.47	0.01*
	Matched	0.138	0.109	0.92	0.36
Electricity supply in house	Unmatched	1.039	1.057	-1.32	0.19
	Matched	1.039	1.042	-0.16	0.87
Value of goats/sheep	Unmatched	5017.700	2929.000	3.81	0.00*
	Matched	4177.300	3612.400	1.07	0.29
Home ownership status (owned or rented)	Unmatched	1.035	1.085	-3.43	0.00*
	Matched	1.035	1.031	0.37	0.71
Consumption of luxury food: beef	Unmatched	0.199	0.190	0.30	0.76
	Matched	0.199	0.205	-0.20	0.84
Percentage of literate adults	Unmatched	39.793	35.025	2.27	0.02**
	Matched	40.081	39.620	0.20	0.84
Number of rooms in house	Unmatched	2.268	2.211	0.78	0.43
	Matched	2.269	2.280	-0.13	0.89
Consumption of staple food	Unmatched	6.480	6.626	-3.40	0.00*
	Matched	6.485	6.559	-1.49	0.14
Availability and type of toilet	Unmatched	1.652	1.559	2.99	0.00*
	Matched	1.651	1.633	0.52	0.61
Stock of wheat held	Unmatched	23.991	21.806	1.58	0.12
	Matched	23.854	23.770	0.06	0.96

The *t statistics* tests equality of the two samples before and after matching. The null states that the mean of a covariate in the control and treated group are equal (i.e. well balanced). ** and * refers to 5% and 1% rejection of the null hypothesis respectively. Of the 18 covariates, 11 are not balanced before matching. All covariates are well balanced after matching. All computations are performed using ‘pstest’ function available on stata.

Appendix 3-B: Overall imbalance testing

Sample	Bias Summary Statistics				Pseudo R^2	*LR*	*Bias*
	Mean	S.D	Skew	Kurt			
Unmatched	13.78	10.10	0.66	2.99	0.068	103.59 (0.00)	13.8
Matched	3.89	3.23	1.01	3.27	0.010	12.60 (0.82)	3.9

The pseudo R^2 falls after matching indicating the covariates are jointly well balanced. The function 'pstest' has been implemented to produce this table.

Appendix 4: List of districts surveyed along with breakdown by borrowers and non-borrowers

No.	District	Non-Borrowers	Borrowers	Total
1	Chakwal	69	54	123
2	Khushab	75	27	102
3	Gujranwala	22	34	56
4	Chiniot	54	11	65
5	Lahore	71	31	102
6	Kasur	77	91	168
7	Sahiwal	38	17	55
8	Muzaffargarh	36	21	57
9	Bahawalpur	46	70	116
10	R.Y.Khan	76	50	126
11	Rajanpur	105	57	162
	Totals	**669**	**463**	**1,132**

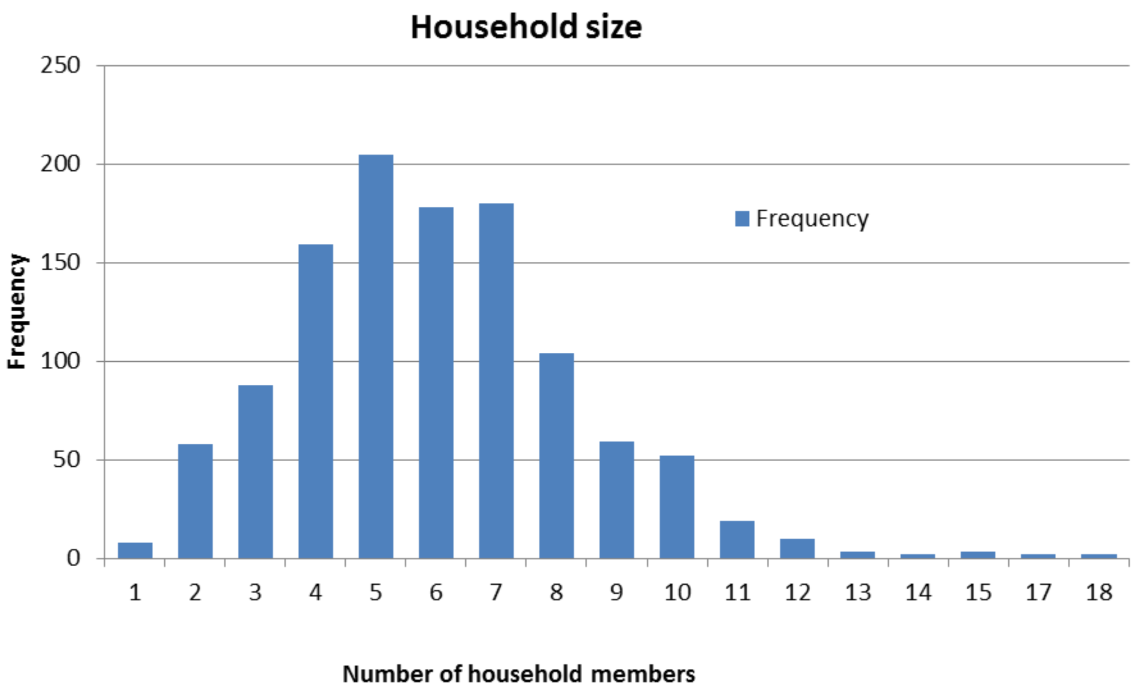
Source: Survey data

Appendix 5: Distribution of principal occupations among survey participants

Sector/Occupation	Borrower Households		Non-Borrower Households		Grand Total
	Frequency	% age	Frequency	% age	
Casual labour	102	22.03	262	39.16	364
Self-employed in non-agriculture-related activities	148	31.97	175	26.16	323
Self-employed in agriculture-related activities	134	28.94	111	16.59	245
Salaried	67	14.47	99	14.80	166
Retired/unable to work or unemployed	12	2.59	22	3.29	34
Total	**463**	**100.00**	**669**	**100.00**	**1132**

Source: Survey data

Appendix 6: Distribution of household size among survey participants



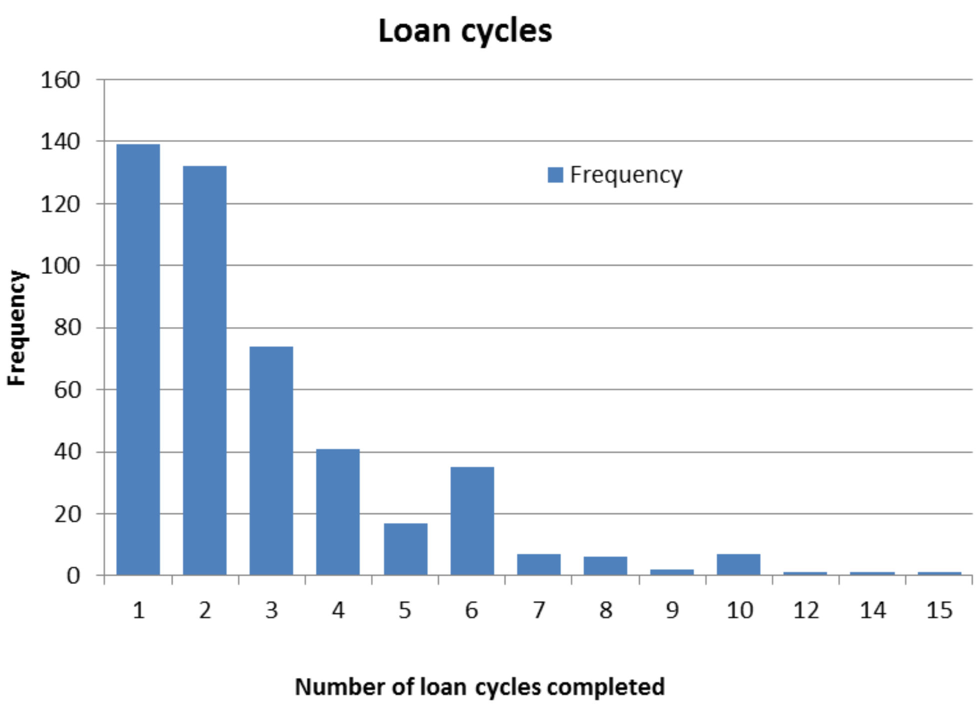
Appendix 7: Distribution of institutional participation among survey participants

Microfinance Institution	1	2	3	%	Grand Total
National Rural Support Programme (NRSP)	153	4	1	31.66	158
Kashf Foundation	138	2	0	28.06	140
Punjab Rural Support Programme (PRSP)	67	2	2	14.23	71
Khushhali Bank	39	0	0	7.82	39
Pak Oman Bank	25	0	0	5.01	25
CSC	22	8	3	6.61	33
1st Microfinance Bank	13	2	1	3.21	16
Asasah	6	8	3	3.41	17
Total	**463**	**26**	**10**	**100**	**499**

Appendix 8: Number of loan cycles completed by respondents at the time of interview

Number of Loan Cycles Completed														
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**12**	**14**	**15**	**Total**
Frequency	139	132	74	41	17	35	7	6	2	7	1	1	1	**463**
Percentage	30.02	28.51	15.98	8.86	3.67	7.56	1.51	1.30	0.43	1.51	0.22	0.22	0.22	**100.00**

Appendix 9: Distribution of survey respondents showing loan cycles completed



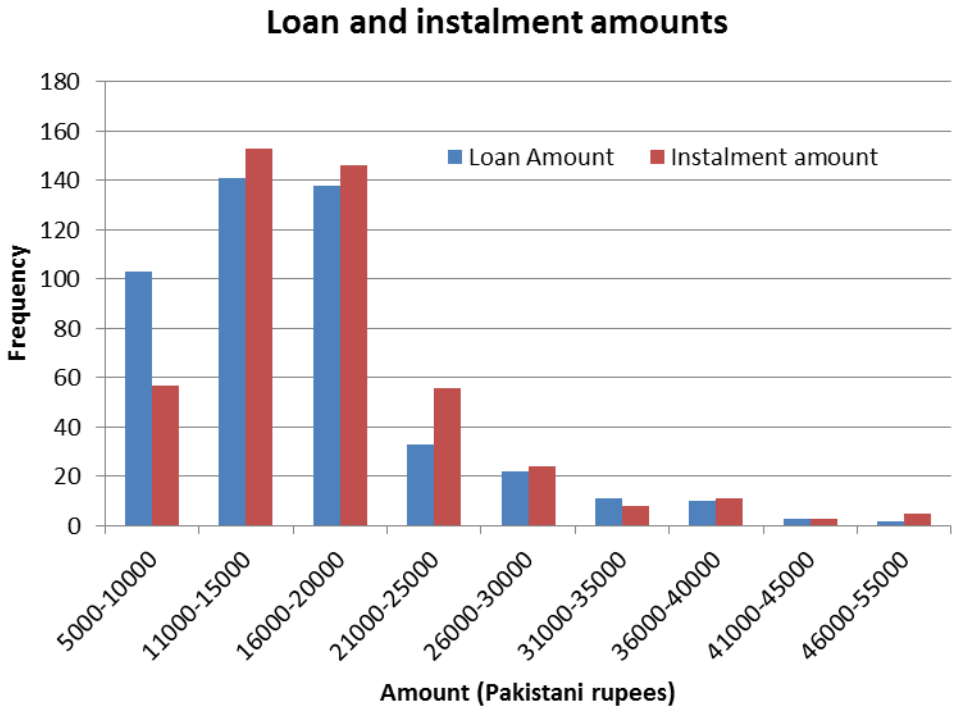
Appendix 10: Basic indicators showing loan use and satisfaction among survey participants

Indicators	Frequency	Percentage
Purpose of obtaining credit		
New business	202	43.63
Expansion	261	56.37
Was the loan beneficial?		
Yes	375	80.99
No	88	19.01
Plans for future borrowing		
Yes	346	74.73
No	80	17.28
Not sure/will think about it	37	7.99
Missed payments		
No	458	98.92
Yes	5	1.08

Appendix 11: Loan sizes and instalment amounts of borrowers interviewed

Loan Amount (Pakistani Rupees)	Frequency	Percentage	Instalment Amount (Pakistani Rupees)	Frequency	Percentage
5000-10000	103	22.25	0-1000	57	12.31
11000-15000	141	30.45	1001-1500	153	33.05
16000-20000	138	29.81	1501-2000	146	31.53
21000-25000	33	7.13	2001-2500	56	12.10
26000-30000	22	4.75	2501-3000	24	5.18
31000-35000	11	2.38	3001-3500	8	1.73
36000-40000	10	2.16	3501-4000	11	2.38
41000-45000	3	0.65	4001-4500	3	0.65
46000-55000	2	0.43	4501-5500	5	1.08
Total	**463**	**100**	**Total**	**463**	**100**

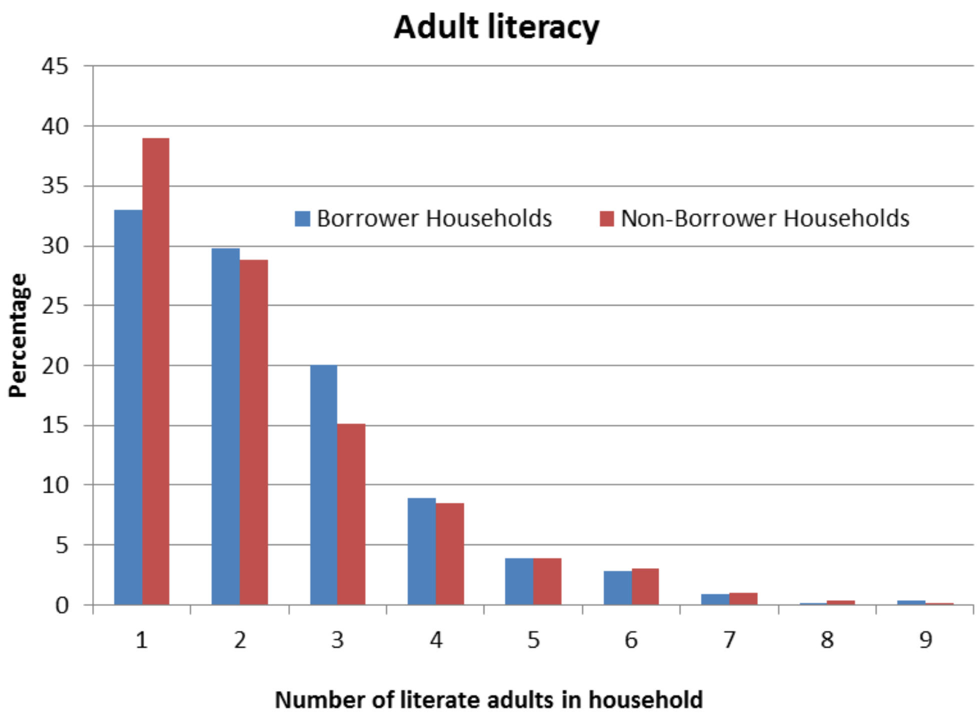
Appendix 12: Loan sizes plotted against instalment amounts



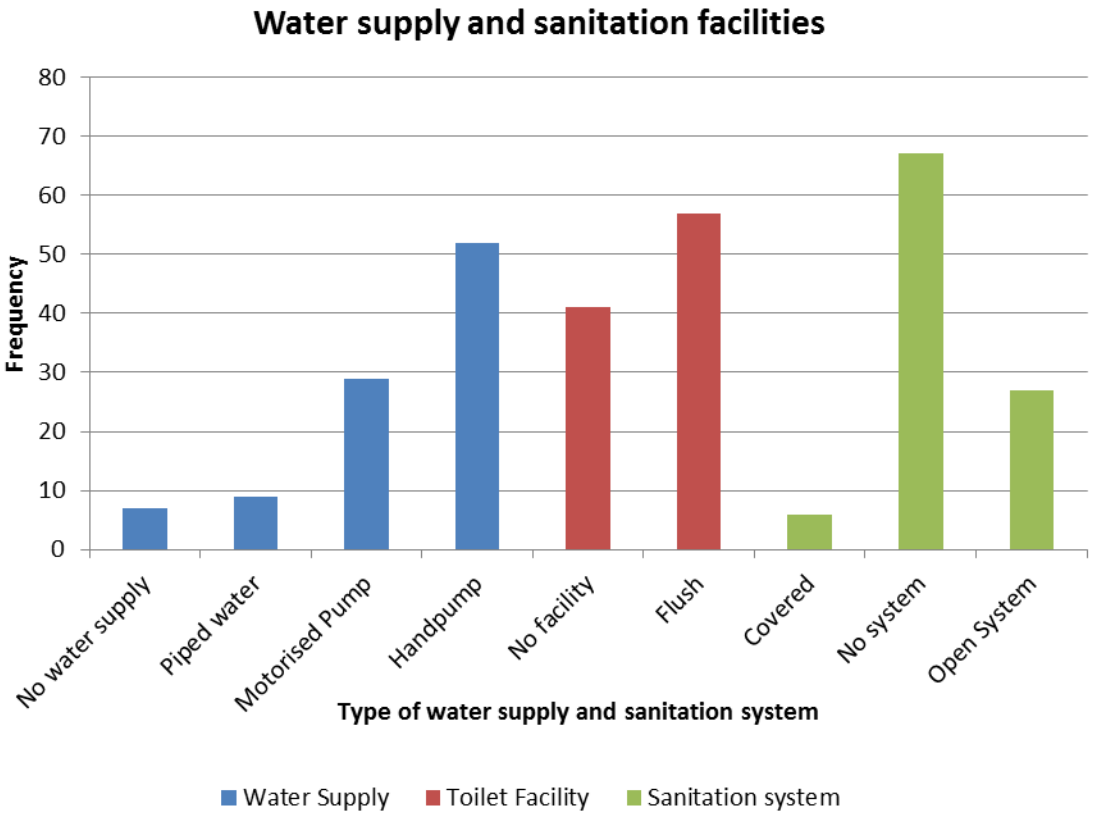
Appendix 13: Adult literacy across both groups of respondents

Number of literate adults in household	Borrower Households		Non-Borrower Households		Grand Total	
	Frequency	% age	Frequency	% age	Frequency	% age
0	153	33.0	261	39.0	414	36.6
1	138	29.8	193	28.8	331	29.2
2	93	20.1	101	15.1	194	17.1
3	41	8.9	57	8.5	98	8.7
4	18	3.9	26	3.9	44	3.9
5	13	2.8	20	3.0	33	2.9
6	4	.9	7	1.0	11	1.0
7	1	.2	3	.4	4	0.4
8	2	.4	1	.1	3	0.3
Total	**463**	**100.0**	**669**	**100.0**	**1132**	**100.0**

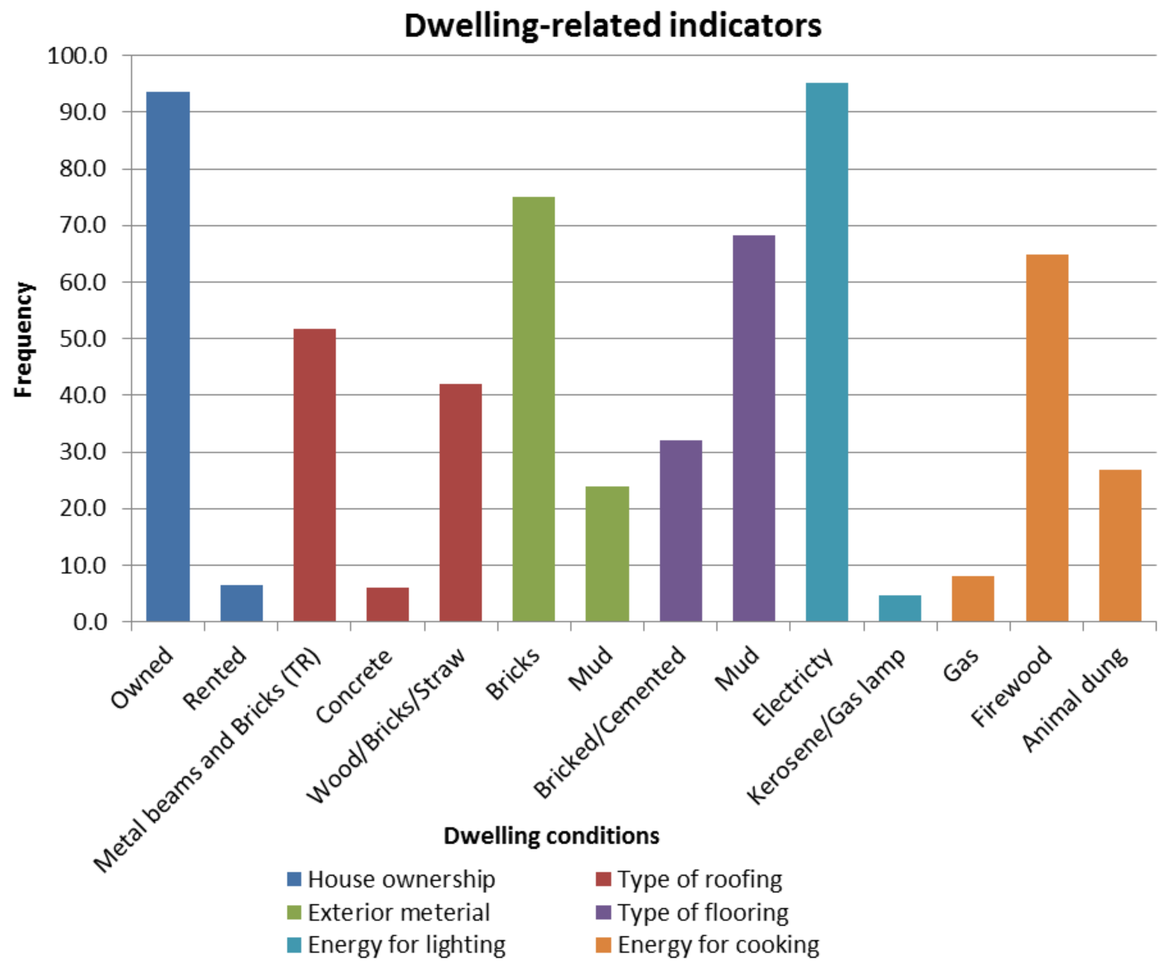
Appendix 14: Comparison of borrower and non-borrower households for adult literacy



Appendix 15: Types of water supply and sanitation facilities available to survey respondents



Appendix 16: General dwelling conditions of surveyed respondents



Dwelling-related indicators
Frequency
100.0
90.0
80.0
70.0
60.0
50.0
40.0
30.0
20.0
10.0
0.0
Owned
Rented
Metal beams and Bricks (TR)
Concrete
Wood/Bricks/Straw
Bricks
Mud
Bricked/Cemented
Mud
Electricty
Kerosene/Gas lamp
Gas
Firewood
Animal dung
Dwelling conditions
House ownership
Type of roofing
Exterior meterial
Type of flooring
Energy for lighting
Energy for cooking

Endnotes

[i] The field survey was carried out by one of the authors between 2008 and 2009. The questionnaire and further details of the survey will be furnished on request.
[ii] For administrative purposes, Pakistan is divided into four provinces and a Federal Capital. Each province comprises several districts, further divided into *tehsils* as administrative divisions. As entities of the Local Government, tehsils exercise certain fiscal and administrative powers over the villages and municipalities within their jurisdiction.
[iii] Methodological issues and programs for propensity score matching estimation are discussed in detail in a number of studies, such as Becker and Ichino (2002), Dehejia (2005), Dehejia and Wahba (2002), Smith and Todd (2005), Todd (2008) and Ravallion (2008).
[iv] Stratification matching is based on splitting the predicted propensity score within the common support region into intervals in a way that in each interval there are treated and controls, while Kernel matching is a non-parametric algorithm that uses weighted averages of almost all the individuals in the control group to construct the counterfactual outcome. See Becker and Ichino (2002) or Caliendo and Kopeinig (2008) for more details.