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 1132 households, including both borrower and non-borrower households, in 2008 – 2009. Sample selection biases have been partially controlled for 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 and household income, and on certain dwelling characteristics, such as water supply and the quality of roofing and walls.*

JEL Classification: C21, G21, O15

1. **Introduction**

Poor households in 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, in which financial services are provided not through traditional routes, such as local moneylenders, cooperatives and banks, but through NGOs or microfinance institutions (MFIs). Microfinance has evolved, and expanded from its origins in 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, which have neither physical collateral nor credit history, can be improved if they are provided with access to small-scale loans or other related financial services, such as savings and insurance.

While a few empirical studies at the micro level have shown that participants in microfinance programmes have progressively become capable of accessing other financial services and escaping from poverty (Hossain & Zahra, 2008; Matin *et al.*, 2008), the wider literature on impact evaluations of large-scale programmes has revealed mixed and

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conflicting findings, with some disagreement amongst academics and practitioners about the effectiveness of microfinance as a poverty-reduction measure. At one end of the spectrum lie studies that have concluded that microfinance is a positive and effective mechanism for poverty reduction (e.g. Hossain, 1988; Barnes, 2001; Dunn, 2002; Snodgrass & Sebstad, 2002; Goldberg, 2005; Khandker, 2005; Haseen, 2006; Rabbani *et al.*, 2006; Mahjabeen, 2008; Banerjee *et al.*, 2009; Imai *et al.*, 2010; Imai & Azam, 2012). At the opposite end are studies which argue 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 & 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 *et al.*, 2009; Karlan & Zinman, 2009; Duvendack & Palmer Jones, 2012). Regardless of the different and apparently contradictory conclusions that have been derived from these empirical studies, which might reflect the diverse settings of the studies (as they focus on different geographical areas and draw 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 & Hussain, 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, income levels. 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 & 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 a given period.

The multidimensional 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% of the population resides in rural areas and is directly or indirectly linked to agriculture (World Bank, 2002; Central Intelligence Agency, 2010). The FAO (2009) estimates that around 66% 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%, more than double that in urban areas. Furthermore, 80% of the total population in poverty live in rural areas (International Monetary Fund, 2010). According to 2007 – 2008 estimates, 22.3% of the country’s population lives below the poverty line, with another 20.5% living in vulnerable conditions (Haq, 2008).

The limited access to financial services in the developing world is a major obstacle to both income generation and social protection. Nenova *et al.* (2009) report that nearly 50% of Pakistan’s population does not engage with either formal or informal financial systems and an estimated 30% 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% 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 Pakistan Microfinance Network estimates, is close to 27 million individuals (Haq, 2008). A study by Ghalib (2013) revealed that the poorest are being significantly under-served 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 desirable to rigorously assess the impact that the model has on livelihoods in the Pakistan setting.

Studies that empirically assess the impact of microfinance at the household level are few, despite the increasing involvement of MFIs in various poverty-reduction programmes. The present study aims to address this gap and provide evidence on the relationship between 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 – 2009 by interviewing 1132 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. Sample selection biases are partially controlled for by matching propensity scores. The findings reveal that despite borrowers seemingly faring better than non-borrowers on around 70% of the indicators, a majority of these findings 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 the 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.

1. **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 11 districts across the rural parts of Punjab in Eastern Pakistan. The study is based on a quasi-experimental design survey1 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 1132 respondents comprises 463 borrowers and 669 non-borrowers. Our broad research question asks 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 rather than 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 are fully representative of the diverse population across the entire province. Starting from the North of the province, districts were selected in the East, West and South. In the second stage, at least one tehsil2 was randomly selected from each identified district. In the third stage, at least two villages were selected randomly from amongst the selected tehsils and in the fourth and final stage; participating and non- participating households were selected at random to be surveyed.

* 1. ***Selection and Choice of Indicators Applied***

Due to the multidimensional nature of poverty (Armendariz & Morduch, 2005; Daley- Harris, 2006), it is necessary to ensure that the dimensions and accompanying indicators examined 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.

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. An important role that household assets play during “lean” periods is helping households to cope with adverse conditions when incomes are low and unstable, 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 some indicators were consequently altered to allow for local specificities. This ensured that the indicators fully captured and reflected the relative poverty levels of both groups of households. Indicators which were highly contextual and affected by subjective responses were then 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. These indicators capture the overall performance of households who joined the MFI programme as well as those who did not.

* 1. ***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, its borrowers represented almost 32% of the total sample. The Kashf Foundation’s strong presence and extensive outreach in the

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 house  Source of water supply  Type of toilet.  Method of bathroom waste disposal  Energy for lighting in 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, cart)  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 to make 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 them to arrive at the most accurate figures rather than making random guesses. Likewise, monthly household expenditure was also added up as they went through the various types of expenditures they incurred in a typical month.

districts surrounding the provincial capital gave it a share of 28%, and the Punjab Rural Support Programme covered 14% of those interviewed. In terms of the number of loan cycles that respondents had completed at the time of interview, almost 60% were found to be within their first two years of borrowing, while 16% were in their third cycle. In terms of principal occupation, although the largest group of respondents was involved in casual labour, at over 32%, there is a significant disparity when data are disaggregated across borrowers and non-borrowers. That is, 22% of borrowing households reported their occupation as casual labour, as opposed to almost 40% of non-borrowing households.

For social and cultural reasons, extended families are common in Pakistan, particularly in rural areas. The most commonly occurring size of household (the 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% 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% of the sample. The national average household size is 6.58 members, according to the Household Integrated Economic Survey (GoP [Government of Pakistan], 2009a), while

Table 2. Average treatment-on-treated effect (ATT) and *t*-statistics across various dimensions and associated indicators

KERNEL STRATIFICATION

Variables *ATT SE ATT SE*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Livestock |  | | | |
| Poultry | 169.290 | 104.322 | 174.258 | 121.757 |
| Cows | 4525.100 | 4532.562 | 4255.300 | 5294.953 |
| Total livestock value | 5665.367 | 4808.349 | 5328.299 | 5163.413 |
| Transport-related assets |  |  |  |  |
| Motorcycle | 2846.157 | 1118.940 | 2823.210 | 996.614 |
| Bicycle | 137.090 | 90.074 | 153.000\* | 83.148 |
| Carts | 2271.837 | 1351.592 | 262.247 | 1075.545 |
| Total transport assets value | 2980.905 | 1747.237 | 2732.457 | 1386.910 |
| Savings |  |  |  |  |
| ROSCA (participation in schemes) | 0.080\*\*\* | 0.020 | 0.077\*\*\* | 0.021 |
| Total ROSCA Encashment Amount | 1675.882 | 1481.425 | 1711.212 | 1277.883 |
| Appliances and electronics |  |  |  |  |
| Mobile phones | 2108.687 | 133.806 | 2111.774 | 134.404 |
| Radio | 287.670 | 54.052 | 283.820 | 53.863 |
| Sewing machine | 32.840 | 90.862 | 21.869 | 83.368 |
| TV | 333.491 | 207.724 | 277.762 | 206.115 |
| VCR | 210.450 | 64.737 | 214.666 | 72.047 |
| Washing machine | 285.733 | 157.823 | 287.321 | 150.746 |
| Total appliances and electronics | 86.332 | 670.348 | 219.079 | 734.958 |
| Value of assets per person | 622.385 | 1065.793 | 452.492 | 1010.307 |
| Total value of household assets | 4770.794 | 5652.850 | 4576.764 | 4806.106 |
| Human development indicators |  |  |  |  |
| Per capita expenditure on clothing and | 109.157\*\* | 49.988 | 102.660\*\* | 44.662 |
| footwear |  |  |  |  |
| Clothing and footwear expenses per annum | 592.458\*\* | 252.431 | 578.518\*\* | 292.586 |
| Clothing expenditure: percentage of income | 20.181 | 0.260 | 20.213 | 0.233 |
| Clothing expenditure: percentage of | 0.465 | 0.348 | 0.399 | 0.325 |
| expenditure |  |  |  |  |
| Monthly expenditure on healthcare | 153.263\*\*\* | 37.834 | 149.656\*\*\* | 42.021 |
| Children currently at school | 20.013 | 0.106 | 20.029 | 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 | 1302.202\*\*\* | 387.241 | 1300.359\*\*\* | 439.474 |
| Dwelling-related indicators |  |  |  |  |
| Type of cooking fuel used | 0.084 | 0.064 | 0.099 | 0.076 |
| Material used for constructing floors | 20.034 | 0.047 | 20.039 | 0.045 |
| Overall condition of house | 0.037 | 0.042 | 0.024 | 0.048 |
| Material used for constructing roof | 20.144\*\* | 0.060 | 20.140\*\* | 0.066 |
| Material used for constructing walls | 20.128\*\* | 0.055 | 20.127\*\* | 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 |

*Note*: SE, standard errors.

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%).

*Source*: Survey data.

the average for Punjab was reported as 6.33 members for 2007 – 2008, close to the mean (5.98) and median (6.00) values reported in the survey results.

In terms of loan size, 22% of respondents had availed themselves of loans ranging from 5000 Pakistani rupees3 to Rs. 10 000, and 30% 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 corresponded proportionately to the size of loans; it was noted that over 60% of the instalment amounts varied from Rs. 1000 to Rs. 2000 with the next biggest share accounted for by smaller amounts of up to Rs. 1000, while larger amounts that ranged from Rs. 2000 to Rs. 2500, accounting for almost a quarter of the total sample. The sample mean is Rs. 17 473, and the median value Rs. 15 000.

The literacy rate, according to the Pakistan Social & Living Standards Measurement Survey (PSLM) for 2007 – 2008 (for both males and females, aged 10 and above), was 56% at the national level and 53% 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%, while according to PSLM (2007 – 2008) it was 40.02%. UNESCO’s Asia-Pacific Literacy Data Base (2009) estimates Pakistan’s adult literacy rate at 54.9% (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 within rural Punjab, the province of this study. According to the PSLM survey, 18% of the total households in rural parts of Punjab have access to piped water, 44% use hand pumps and 35% have motorised pumps in their homes. These figures were close to those obtained by the survey carried out for this study, in which 53% reported using hand pumps and 30% had motorised pumps. Data published by PSLM for access to toilet facilities revealed that 51% had access to flushed toilet systems and 49% did not have any facility at all. The survey for this study found 57% and 42% for the two classes, respectively. Data for drainage systems consisted of three categories: covered, open and no facility, reported by our survey at 6%, 27% and 67%, 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% of respondents owned the houses in which they were living. Roofing structures were dominated by metal beams and bricks at 52%, followed by wooden beams and bricks at 42%. Only 6% of the houses had concrete roofs. For construction of exterior walls, bricks were used in 75% of the cases, and mud for the remaining 25%. Mud was more commonly used as a flooring material (68%) as opposed to the brick or cement floors found in the remaining 32% of houses. Electricity for lighting was reported at over 95%. The most common type of energy used for cooking was firewood (65%), followed by animal-dung cakes (the cheapest alternative) at by 27%; only 8% of households used methane gas cylinders.

Finally, the field instrument contained questions designed to capture elements of borrowers’ behaviour, views and attitudes towards credit. In relation to the purpose of obtaining credit, 43% stated that it was for establishing a new business, while 57% reported it would be used for expanding existing businesses. When asked about the usefulness of the loan, around 81% expressed satisfaction, but 19% reported not finding it beneficial. This figure of unsatisfied borrowers matches the proportion of those who had no plans for borrowing in future (17%); around 75% were willing to borrow in the next cycle and around 8% were still undecided at the time of interview. As expected, delinquency was almost absent and the repayment rate was very high (approximately 99%), an indication that borrowers continue to repay regularly, despite any difficulties that they face or any decision not to borrow in the future. What is noteworthy, however, is that “missed” payments were usually paid in the following month, and hence cannot be considered “defaults” per se.4

**3. Modelling methodology**

We measure the impact of treatment on the outcome, ie 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:

 (1)

where  is the treatment effect of individual *i,* in which *i=1,2,…,N.*  and  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) approximates 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 calculate directly, 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, , which can be expressed formally as:

 (2)

 measures the difference between the expected outcome with and without treatment for the actual participants. The term  represents expected outcomes for programme participants, while  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, while the term  cannot be estimated since it is not observed. An alternative way to estimate  is to use the mean outcome of untreated, , as an approximation for . If the approximation  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 leading to a selection bias problem. This implies that equation (2) is described as:

 (3)

where the term  measures the size of the bias due to unobservables. Thus, the 'true' value of the average treatment of the treated, , can be identified when the bias is zero, or:

 (4)

When the bias is due to observables, we face a scenario known as *self-selection bias,* which is caused by the fact that participants themselves decide whether to join the programme and thus the probability of participation by individuals in the sample is non-random

The literature suggests a number of approaches to handle this bias. One approach is to implement matching procedures, such as covariate matching (as in Rubin 1973) and propensity scores as suggested by Rosenbaum and Rubin (1985) (RR, hereafter), which use available information for non-participants’ to estimate the impact. In this context, the Propensity Score Matching (PSM) approach proposed by RR 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 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 the explanatory variables of the treatment and control groups overlap relatively little; and it does not require a valid set of instruments[[1]](#footnote-1). Moreover, the matching approach (e.g. PSM) does help to eliminate much of bias associated with unobservables. Indeed, replication studies comparing non-experimental evaluations, such as PSM, with experiments for the same programmes have found more or less consistent results based on these two different methods. 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 a 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 called ‘the stable unit treatment value assumption’ (SUTVA) in which one’s counterfactual stats do not depend of the treatment status of other individuals holds in this paper (see Rubin (1980, pp.20-21). 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 that it rules out the possibility of peer and general equilibrium effects.

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 due only 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 is defined formally as:

*Assumption* 1.A:  (5A)

where '' 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 a positive probability of being participants and non-participants. In order to achieve this condition, one needs to define the following overlap condition:

*Assumption* 2.A:  (6A)

The overlap condition rules out the perfect predictability of participation conditional on the characteristics identified by the set of covariates *X.*

These two assumptions combined allow us to estimate the effect of treatment on the treated,. The two assumptions, as argued by Imbens (2004), can be relaxed when estimating[[2]](#footnote-2):

*Assumption* 1B:  (5B)

*Assumption* 2B:  (6B)

The weaker version of the 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. RR introduce what is known as a balancing score to avoid the problem of high dimensionality. The balancing score suggested by RR 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:

 (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 based on their personal characteristics. Following much of the literature, equation (8) is specified as a probit model and expressed as follows:

(9)

where , for all values of covariates *X* ,  and  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 of treatment, given the set of covariates *X* such that:, 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.). Therefore, the PSM estimator of  is selection-bias free. Formally, the PSM estimator defined is as:

 (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[[3]](#footnote-3), which are widely used in the literature. Using two matching algorithms avoids some of the shortcomings that may result from relying on a single method, and it also helps to check the robustness of the estimated impact.

* 1. ***PSM Estimates: General Discussion***

Appendix A 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.

Amongst the explanatory variables, electricity supply in the house, home ownership, and 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 the child dependency ratio, instances of child labour and availability and type of toilet had a positive and statistically significant effect on the probability of borrowing or joining the programme; these findings may indicate that when household members are experiencing deprivation, it encourages one of the members to borrow to set up a small family-run business.

Distribution of the estimated propensity score of all the households resulted in some seven observations being dropped from the matching procedure since they lay outside the overlap region. This is shown in Appendix B, 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 and 11 overlaps 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 the treated group and the control group at the 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 C.1 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 C.1 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 C.2 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 likelihood ratio (LR) statistic since we accept the null with p-value equal to 0.82 and the model is jointly significant before matching since we accept the alternative hypothesis having an LR statistic with p-value equal to zero. In addition, matching reduces the bias by a significant magnitude from 13.8 before matching to 3.9 after matching.

1. **Survey Findings: The Economic and Social Impact of Microfinance**

The sections above discussed the methodology and procedures adopted to control for any selection biases in the sample. 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 for each dimension, statistically significant values provide strong evidence that disparities between the two groups did not occur merely by chance, but are attributable to programme participation.

* 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 undertaken 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, which is of low 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 of 1.50. The ATT for cows was positive and large, but not statistically significant and does 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 the saving behaviour of respondents was participation in ROSCA (Rotating Savings and Credit Association) schemes, which are a form of informal saving model found in many parts of the world, although 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 showed a much higher probability and incidence of participation in ROSCA schemes than did non- borrowers. Moreover, there was an average difference (ranging from Rs. 1723 to Rs. 1545, across kernel and stratification methods) in the payout amount of the ROSCA, with borrowers saving greater amounts and, as would be expected, contributing more (around Rs. 105 monthly) towards the saving scheme. A possible explanation is that once rural households start to participate in microcredit programmes they develop a sense of the possibilities arising from financial access and realise the importance of participating in saving schemes. In the absence of formal options, they resort to semi-formal institutions (such as ROSCA, in this case) and commit a certain amount to be contributed to the schemes.

As opposed to the impact of borrowing on the ownership of livestock, that of borrowing on ownership of 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, while non-borrowers seemed to fare slightly better in terms of owning radios. Borrowers, however, seemed to be better off in the ownership of televisions (with an 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 when 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 was not statistically significant.

* 1. ***Human Resources***

Our survey questionnaire also captures various demographic characteristics of household members, household income and the amount spent on clothing and footwear, children’s schooling and healthcare. Data on clothing and footwear expenditure show 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.

* 1. ***Household Income and Expenditure***

Table 2 portrays the differences between both groups of respondents in terms of monthly household income and expenditure. Although the difference in overall monthly household expenditure is not statistically significant, the difference in 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 household expenditure is small (varying from Rs. 220 to Rs. 239 across matching methods), whereas the difference in household income is both substantial (given that the sample’s median income is Rs. 7500) and statistically significant at the 1% level. Depending on the matching method used, the monthly income of borrowers is greater by Rs. 1300 (stratification) and Rs. 1302 (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 and cart. Moreover, 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 or a bicycle repair shop, buying a donkey-cart, purchasing a cow or selling an existing one and “upgrading” to a better breed.

* 1. ***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 and 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 evidence 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.

1. **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 the relative well-being of a typical rural household in Pakistan. Household characteristics were captured across four dimensions, further divided into various indicators, the data on which were gathered by administering a semi-structured questionnaire in the field. The research was based on a 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 PSM model was applied, through which the ATT was 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 insignificant 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, while 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 between the groups favoured borrowers, and were observed in savings, television ownership, 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% of the indicators on 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 spent 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 limited in magnitude. This study leads us to infer that continued sustained efforts would enlarge the positive impact given the limited access to financial services in Pakistan, the low penetration of MFIs and their consequent potential to expand their coverage. MFIs in the country can achieve greater reach and impact by diversifying their product mix and tailoring products to suit seasonal needs. Flexible repayment terms could also be beneficial to the rural poor in order to suit their seasonal and variable income streams.

The present study assesses the impact of borrowing from MFIs on various dimensions of livelihoods across parts of rural Punjab in Pakistan. It would be enlightening to extend the study to the country’s three other provinces. Such studies on a national scale could contribute towards a better distribution of development funds.

Notes

1 As noted, the field survey was carried out by one of the authors between 2008 and 2009. The questionnaire and further details of the survey can be furnished on request.

2 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 entitiesof the local government, *tehsils* exercise certain fiscal and administrative powers over the villages and municipalities within their jurisdiction.

3 1.00 USD ¼ 102.870 PKR.

4 Further charts and tables describing various components of the survey are available from the authors upon request.

5 Methodological issues and programmes for propensity score matching estimation are discussed in detail

in a number of studies, such as Becker & Ichino (2002), Dehejia (2005), Dehejia & Wahba (2002), Smith & Todd (2005), Todd (2008) & Ravallion (2008).

6 Stratification matching is based on splitting the predicted propensity score within the common support region into intervals in such 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 & Ichino (2002) or Caliendo & Kopeinig (2008) for more details.

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

Variables Probit estimates Marginal effects

|  |  |  |
| --- | --- | --- |
| Intercept | 1.199 (0.762) | 20.013 |
| Value of agricultural land | 20.033 (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) | 20.030 |
| Type of occupation 3 | 20.079 (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) | 20.120 |
| Electricity supply in house | 20.310\* (0.184) | 4.99e-6 |
| Value of goats/sheep | 1.29e-5\*\*\* (4.88e-6) | 20.174 |
| Home ownership status (owned or rented) | 20.449\*\* (0.175) | 20.093 |
| Consumption of luxury food: beef | 20.240\*\* (0.109) | 0.001 |
| Percentage of literate adults | 0.002 (0.001) | 20.017 |
| Number of rooms in house | 20.044 (0.036) | 20.076 |
| Consumption of staple food | 20.198\*\*\* (0.076) | 0.061 |
| Availability and type of toilet | 0.159\* (0.081) | 20.002 |
| Stock of wheat held | 20.005\*\* (0.002) | 20.013 |

*Note*: Values in parentheses are standard deviation. Sample size is 1132. The log likelihood ratio of the probit model is LR ¼ *103.59* [ *p*-value ¼ 0.00]. *R* 2 ¼ 0.07. The model is estimated using STATA’s “probit” function.

\*\*\*1% level of significance, \*\*5% level of significance, \*10% level of significance.

Appendix B: Balancing property test by block

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| ***Block 1:*** | | | | |
|  | 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:*** | | | | |
|  | 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:*** | | | | |
|  | 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:*** | | | | |
|  | 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:*** | | | | |
|  | 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:*** | | | | |
|  | 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 being a difference. All computations are performed using STATA’s function “pscore” developed by Becker & 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” redo 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 C.1: 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 |

*Note*: 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). Of the 18 covariates, 11 are not balanced before matching. All covariates are well balanced after matching. All computations are performed using the “pstest” function available on stata.

\*\* and \* refer to 5% and 1% rejection of the null hypothesis, respectively.

Appendix C.2: Overall imbalance testing

Bias Summary Statistics

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Sample | Mean | SD | Skew | Kurt | Pseudo *R* 2 | LR | Bias |
| 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 |

*Note*: The pseudo *R* 2 falls after matching, indicating the covariates are jointly well balanced. The function “pstest” has been implemented to produce this table.

1. Methodological issues and programmes 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). [↑](#footnote-ref-1)
2. [↑](#footnote-ref-2)
3. Stratification matching is based on splitting the predicted propensity score within the common support region into intervals in such 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. [↑](#footnote-ref-3)