EVALUATION OF MICROFINANCE INSTITUTIONS IN PAKISTAN: USING ECONOMETRICS TECHNIQUES

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PIDE2019FMPHILETS05

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(PIDE), ISLAMABAD

2023

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CERTIFICATE

This is to certify that this thesis entitled **"Evaluation of Microfinance Institutions in Pakistan: Using Econometrics Techniques"** submitted by **Mr. Zahanat Hussain** is accepted in its present form by the School of Economics, Pakistan Institute of Development Economics (PIDE), Islamabad as satisfying the requirements for partial fulfillment of the degree in Master of Philosophy in Econometrics.

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Author's Declaration

I Zahanat Hussain hereby state that my PhD thesis titled "**Evaluation of Microfinance Institutions in Pakistan: USING ECONOMETRICS TECHNIQUES** is my own work and has not beensubmitted previously by me for taking any degree from Pakistan Institute of Development

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Date: March 15, 2023

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Table of Contents

ABSTRACT

Microfinance is known as a direct and indirect contributor to the welfare of the poor in Pakistan. Data from the Pakistan Bureau of Statistics (PBS) Household Integrated Economic Survey (HIES) for the year 2018-19 has been used in this study.

An Econometric approach called "Propensity score matching (PSM)" technique have grown incredibly over the past decades. They are used primarily to match treatment and control units to estimate the causal treatment effect from observational studies or to link two or more data sets that share a common subset of covariates. This study analyzes the impact of microfinance institutions on the well-being of poor people in the literature on microfinance in Pakistan using PSM and matching methods like Nearest Neighbor Matching, Radius Matching, Kernal Method, and Stratification Method.

This study found out that microfinance institutions have a positive impact on poverty reduction and hence it is an effective tool for poverty reduction in many countries including Pakistan. This study found that most of the loan has been used for income-generating activities and many other functions. The Effect of microfinance on household well-being in Punjab, Sindh, and Balochistan has less effect by (-0.094), (-0.084), and (-0.119) coefficient values than KP (0.121) respectively. Propensity score matching (PSM) generated slightly different results. The study also shows that the treatment group who received microfinance had lower income than the control group. The best matching criteria are the Radius matching criteria, which is similar to unmatched difference and has a higher effect on well-being than rest three criteria for example nearest neighbor, kernel matching, and stratification matching criteria. The PSM has been preferred over OLS, DID, and RDD because it does provide us with some households which have similar characteristics.

Keywords: Microfinance, Well-being, Matching, Propensity Score Matching, PSM Technique, Nearest Neighbor, Kernal matching, Radius matching, Stratification matching

LIST OF TABLES & GRAPHS

LIST OF ABBREVIATIONS

ATE	Average Treatment Effect
ATT	Average Treatment Effect with Treated Group
α	Alpha
β	Beta
HHW	Household Well-being
HHI	Household Income
HIES	Household Integrated Economic Survey
PBS	Pakistan Bureau of Statistics
ETS	Department of Econometrics and Statistics
MFI	Microfinance Institution
NN	Nearest Neighbor
PIDE	Pakistan Institute of Development Economics
PSM	Propensity Score Matching
SE	Standard Error

CHAPTER NO 1

INTRODUCTION

The development program was initiated by Muhammad Yunus, a Bangladeshi economist who was famous for establishing the Grameen Bank. Microfinance institutions are the most unique and prominent in poverty alleviation that provide small loans to poor people without collateral (Yunus, 1999). The main idea of microfinance services is to provide financial support through microfinance institutions to deprived poor when they need it in a very comfortable condition (Rehman, 2007). The concept of microfinance has been emphasized in both policy-making and academic discussions after decreasing the poverty rate in developing countries, especially in Bangladesh. Many reasons need for microfinance arise, one of which is poor people have been neglected by other banks (commercial) because they are economically active but financially weak and Limited.

The purpose of microfinance institutions (MFIs) is to give loans on a micro level to poor and low-income citizens not including collateral and is mainly performed to initiate and develop “Small and Medium-sized Enterprises (SMEs)”. Which eventually aimed to assist the poor in breaking the poverty cycle. Due to collateral requirements, poor people can’t avail of financial loans from commercial banks, so microfinance institutions provide the poor the basic financial services, like micro-loans, insurance, saving, etc. This developmental program is widely called microfinance.

(Sengupta & Aubuchon, 2008) stated that microfinance is widely recognized as a successful development tool for reducing poverty in low-income countries. Street vendors, small traders, cottage industry laborers, and low-wage earners are the most likely microfinance clients in urban areas. while in rural locations poor need microfinance for agricultural activities (Al Mamun et al., 2013). While microfinance programs are recognized for their ability to increase income and alleviate poverty (Wright, 1999). Due to the profound impact of poverty on the welfare of the poor, efforts have been made by several multilateral organizations such as the United Nations to address these issues and combat poverty (Al Mamun et al.). Around 1.9 billion people, or 36.9 percent of the world's population, were living below US$1.90 per day in 1990. By 2015, this number was estimated to have dropped to 700 million, with an estimated 9.6 percent of the world's population living in poverty. The decline has been the outcome of the majority of development policies and factors executed over the past three decades (Mahembe & Odhiambo, 2018).

Microfinance institutions began in the early 1980s with the purpose to empower the needy and increase their ability to generate revenue. The Aga Khan Rural Support Program (AKRSP) and the Orangi Pilot Project (OPP) were both launched in 1982. Pakistan, although a latecomer to this industry, has made significant progress in microfinance. The Sarhad Rural Support Program (SRSP) and the National Rural Support Program (NRSP) were launched in the 1990s, and a model of AKRSP was adopted across the country. These Non-governmental organizations (NGOs) and Rural Support Programs (RSPs) have made microcredit available in the country. International focus on microcredits at beginning of the new century accelerated the growth of Pakistan's microfinance industry. The Pakistani government helped establish Khushali Bank in 2001, a major retail organization aimed at serving the needy and poor, especially in rural areas (Ahmad, 2011).

Eleven Microfinance Banks, 17 Microfinance Institutions, and 5 Rural Support Programs are working according to Pakistan Microfinance Network members who have reported their organizational data at the time of the 2019 review publishing (Pakistan Microfinance Review, 2019). There are seven specialist microfinance banks, three non-banking financial institutions (NBFIs), and nineteen non-governmental organizations (NGOs) in Pakistan (Khan & Sulaiman, 2015) “names and the list of mentioned banks and institutions in chapter 2 section 2.2”. Around 28% of the credit institutional members in Pakistan are living below the line of poverty in comparison to 41% of those who aren't members of credit institutions (Ahmed et al., 2001). Another author (Khandker, 2005) found a substantial positive impact on the rates of poverty in Bangladesh, he revealed that the poverty rates in urban areas of Bangladesh have dropped by around 18 points in program places and 13 points in non-program places because of the initiation of the MFIs. In this way, MFI not only helps the poor as they participate in MFI but also improves the local economy.

Many programs offer stand-alone the products like savings and insurance is becoming a popular innovation in the combination of services offered by financial institutions for the poor. Microfinance services are no longer limited to poor-serving institutions. Consumer durables companies and businesses are targeting the poor with microcredit programs.

1.1 STATEMENT OF THE PROBLEM

When academics talk about poverty and the well-being of the poor, Microfinance has always been a matter of discussion. Microfinance institutions prevail for a long time and are being developed but poverty still exists in Pakistan. The problem is that MFIs claim that the poverty has declined with micro credits but this study is to review microfinance, and whether these microloans from MFIs help poor in critical situation and reduce poverty and raise the well-being of poor people.

1.2 OBJECTIVES OF THE STUDY:

This study has the following objectives:

- To assess the impact of Microfinance Institutions on the well-being of poor people
- To check the effect of different matching criteria of PSM on results and interpretation
- To assess different matching criteria's impact on microfinance policies/intervention

1.3 RESEARCH QUESTIONS:

- Whether MFI loans are helping reduce poverty and raise the well-being of poor people?
- How different matching criteria of PSM can influence the results and interpretation
- How can the results of different matching criteria affect different policies/interventions of microfinance?

1.4 SIGNIFICANCE OF THE STUDY

The alleviation of poverty, raising living standards, participation of the poor in the market, and a high employment rate are basic requirements for high growth. The significance of the study has examined whether microfinance is benefiting the poor and providing them with business opportunities in rural Pakistan.

1.5 ORGANIZATION OF THE STUDY

The entire study has been organized into seven sections. Following the Introduction, Chapter II reviews the literature on the evaluation of microfinance in Pakistan. Chapter III is about research methodology and discusses the PSM technique and different matching criteria, this chapter also discusses the variables and data. Chapter IV describes Results and Estimations, next chapter V is conclusion and last chapter VIII is “Suggestions and Recommendation”. References have been added in the last portion of the research.

CHAPTER 2

REVIEW OF LITERATURE

MFI started as a non-profit credit-granting institution that aimed to help the poor. “The legal structure, goal, and methods of these organizations differ. MFIs have grown during the 1970s from nongovernmental organizations (NGOs) that provided small loans to the needy to legal financial institutions with vast networks and profit-making purposes. These institutions have a variety of distribution channels, such as automated teller machines, and have made technological investments to provide complex goods and services, such as risk management insurance, money transfers, and pension plans (Goldsmith, 2011).

There is a vast range of literature available on the influence of community-organized loans and saving associations and microcredits on poverty alleviation, and local and community development both in developing and developed economies.

According to (Beyene, 2019) participatory-development substantially improves the efficacy of credit activities at the level of community in poverty alleviation terms. Those respondents who participated went farther in developing awareness and supporting works among a wide range of users regarding the requirement of aimed recipients (poor). Moreover, the author thought that the participation cost is small compared to its benefits. The author further revealed that the user’s participation reinforces the microfinance sustainability and efficacy of every type of poverty alleviation at the level of community

Furthermore, the interventions of MFIs also lead the poor by increasing their income level and their governance of that income, improving their skills and knowledge in trade and production also improving their participation in street vendors and markets (Nyamongo, 2016). Consequently, social perceptions and attitudes may vary, and the status of the poor in households and communities might be improved. Many microfinance institutions give valued services to the needy and poor in emerging countries, thus they have become the most economically accomplished and vibrant urban areas, where the opportunities for investments prosper. The streams of income are diverse and regular and the reach cost of consumers is very low.

Three decades, after the initiation of the MFIs revolution, individuals who live in rural and slum areas and Individuals who are severely deprived, have difficulties in getting access to MFIs' loans and beneficial products (Brannen, 2010). Consequently, most poor people aren't willing to reach financial institutions for credit agreements because of the requirements of credit institutions like collateral or offset capacity of the loan repayment (Bekele & Worku, 2008). Additionally, it has been observed by World Bank that of 193.6 million households that are labeled as poor across the world, only around 48% are those who can hardly access credit institutions (Nyamongo, 2016).

In the past forty years, the eradication of poverty has been linked to the growth of economies all around the world. Empowering the poor involves better access to and control over household resources, including physical and financial assets, increased mobility, and the attainment of skills and knowledge (Osmani, 2007).

After studying previous literature, we assume that the Propensity Score Matching methodology suits best the whole process. For cross-sectional survey data, the PSM technique can be quite beneficial. In observational studies, this method can dramatically reduce bias (Dehejia & Wahba, 2002). The use of Propensity Score Matching is quite new in economics.

With the help of the PSM method, a researcher can match participants from the treatment group and control group, just to balance both the treatment and control group. The PSM technique was established to assist researchers in drawing causal inferences and conclusions from observational studies. The propensity score is a conditional possibility of being assigned to the treatment group for an individual (Rubin & Thomas, 1992). Normally, This technique is usually calculated with Logit and Probit regression, using the participants' covariates as X and the treatment status of the participants as Y (Rosenbaum, 1987). In the Probit model, non-treatment factors such as the background characteristics of the participants are included as covariates. These covariates' information is abstracted by the estimated propensity score. A researcher can link participants in the treatment group to control group participants using estimated propensity scores to facilitate causal inference. Unmatched comparison units are rejected and are not considered in the treatment impact calculation after units are matched, which is an important characteristic of this method.

Much literature has shown the positive impact of microfinance on poverty reduction. There lot of research available in Pakistan on the work of microfinance institutions in reducing poverty and monitoring the welfare of the poor.

(Beyene & Dinbabo, 2019) carried out exploratory research on village loans and saving associations (VLSA) in Ethiopia. The author revealed that VLSA contributes positively to the schooling of children and on social capital, improves the power of decision making, poor people's economic empowerment, concord and peace within the household, improvement of the saving culture, promotes security, social status, social engagement, and the goal for a prosperous future.

(Al Mamun et al., 2013) highlighted various major characteristics of microcredit institutions that distinguish them from commercial banking features. The authors presented key features of the tool of poverty reduction as given below:

- The small size of loan that is ascertained by microfinance institutions
- Emphasize those loaners who have no or negligible access to the credit

- Focus on loan utilization to initiate small enterprises as it provides opportunities for employment
- No requirement for the tangible collateral
- Making of join credit groups to enforce the payment
- Mobilization programs of savings that need loaners to create a saving account and gather financial resources

Among such characteristics, group meetings and training are also necessary tools in microcredit. Once a person chooses to take debt from the microfinance institutions, the person needs to attend all these activities and take part in the capacity development programs. Risk management and entrepreneurship skills, credit-discipline, values creation, and knowledge on hygiene and health, among others, are described and educated in such sessions of pieces of training to understand the loaner with proper information which efficiently conserves his/her small enterprise and assists in everyday life (Dowla & Barua, 2006). Through this technique, microfinance institutions can give both financial capitals and encourage the responsibility sense and drive to accomplish triumph in entrepreneurial-endeavors.

2.1 RESEARCH GAP:

Various researchers try to evaluate different interventions in MFI for different reasons. Like akin good market and client research, checking the return of their investment, impact on participants and repayment process, etc. Many research papers are available on the role of microfinance institutions in poverty reduction addressed by econometric technique called “Proprietary Score Matching” (PSM).

The focus of this research is on the well-being of the poor in rural areas in Pakistan through microfinance. Aa a high percentage of people are still poor and they face difficulties to run small businesses and manage two-time food, health, and education system.

2.2 CONCEPTUAL FRAMEWORK

According to the MFIs' mission statement, it usually targets young people to improve their lives through active participation in productive businesses. Poverty alleviation is an expected goal of the MFI. The main problem of the poor is the unavailability of collateral microfinance which provides a way to facilitate collateral-free loans at a fixed interest rate (Bangoura et al., 2016).

Pakistan's State Bank regulates microfinance institutions. Pakistan is one of the few countries with its own regulatory and legislative framework for microfinance banks. This framework promotes a good and favorable climate to receive microfinance services for the country's most deserving citizens. In recent years, the State Bank of Pakistan (SBP) has taken a variety of steps to support and strengthen this sector

A basic goal of microfinance institutions is to provide a readily accessible micro-credit program for the poor that can substitute and replace pro-poor development. Most researchers reported that MFIs facilitate poverty decline via enhanced life quality on one side and the economic empowerment of women on the other side (Bangoura et al., 2016).

2.3 WHAT IS MICROFINANCE

Microfinance is a type of banking that specializes in providing financial services to low-income individuals and groups that would otherwise be unable to access micro-credit. Microfinance covers all training and support provided by microfinance institutions (MFIs). MFIs provide micro-loans to groups or persons with low incomes individual and families. Before customers may receive their loan, the microloan foundation conducts comprehensive training. This course will explain how and why the loan should be utilized to run a business simply and concisely (microloanfoundation.org.uk, 2021). Microfinance is a program that gives collateral-free loans. It is one of the proposed poverty reduction strategies. It is a type of finance that provides a variety of goods and services, including microloans, insurance, and transactional services to individuals and groups. The target group in this mode is the lower middle class. There are two types of microfinance loans: group loans and individual loans. The mechanism of joint liability is used in group loans. The entire group is held responsible for debt repayment (Nawai & Shariff, 2010). Microfinance in Pakistan has the potential to develop, according to a report by the State Bank of Pakistan (FY06). In Pakistan, there are about 83 microfinance institutions (MFIs) such as Akhuwat, Foundation for International, Community Assistance (FINCA), Advans Pakistan Microfinance Bank, and others operate. MFIs are mainly concerned with helping the poor in their economic and social development.

Microfinance institutions (MFIs) are defined by the Microfinance Ordinance (2001) as an entity that accepts public deposits to provide microfinance services. Microfinance banks play a vital role in building a country’s economy, especially the lower classes. In Pakistan, MFIs include Microfinance Banks regulated by the State Bank of Pakistan, as well as NGOs, RSPs, and CFIs, which are listed below:

2.3.1 Non-Governmental Organizations (NGOs):

NGOs that operate as microfinance institutions, as well as those that run microfinance operations as part of a multi-dimensional development program, fall under this category. MFIs include the

Sindh agriculture and forestry workers Coordination Organizations (SAFWCO), Akhuwat, Orangi Pilot Project (OPP), Kashaf, and Asasah, they are working in Pakistan as microfinance institutions. Microfinance services are provided by Development Action for Mobilization and Emancipation (DAMEN), Taraqi Foundation, and Sungei as part of their overall integrated development services.

2.3.2 Rural Support Program Network (RSPN):

RSPN has a longstanding relationship with the Government of Pakistan. Pakistan's largest development network, reaching over 54 million rural Pakistanis. It consists of 10 members of Rural Support Programs (RSPs) such as the National Rural Support Support Program (NRSP), Punjab Rural Support Program (PRSP), Sarhad Rural Support Program (SRSP), and Thardeep Rural Development Program (TRDP) are currently in existence which has been operating since 1982. RSPs support a common approach to rural development. The (RSPs) undertake microfinance activities as part of their multidimensional rural development agenda (rspn.org, 2022).

2.3.3 Commercial Financial Institutions (CFIs):

Commercial banks are the financial institutions that accept deposits, makes various loan, and offer basic financial products like certificates of deposits and saving accounts to individuals and small businesses. Orix leasing and the Bank of Khyber are examples of CFIs. Microfinance services are provided as a separate function within the broader organizational context by these financial institutions in the mainstream financial sector (Pakistan Microfinance Network Performance Report (2005)).

2.4 Empowerment via Microfinance

Poverty is defined in a variety of ways. It's a complicated phenomenon that's hard to understand and define. While it is most commonly defined in monetary terms as the World Bank's one-dollar-a-day poverty line was established in the 1980s (Townsend, 2006). The new global poverty lines of $2.15, $3.65, and $6.85 reflect the typical national poverty lines of low-income, lower-middle-income, and upper-middle-income, which replaces the $1.90 per person per day poverty line, is based on 2017 PPPs (WorldBank, 2022). There are different number of income groups including lower-middle to upper-middle which attracted many of the microfinance institutions to set up a base.

Credit is seen as linked to the empowerment of the poor. Microfinance enhances poor people's income and control over it, improves their knowledge and abilities, and boosts their participation in the competition and the market. It all brings about change in society, social attitudes, and perceptions.

2.5 Conclusion of Literature Review:

After studying the literature, the researcher has chosen “Propensity Score Matching” as it is the best to fit model for this study instead of Ordinary Least Square (OLS), Regression Discontinuity Design (RDD), Difference in Difference Method (DID), instrumental variables (IV) and Synthetic Control Method (SCM), etc. PSM is the best technique for cross-sectional data and estimating the causal treatment effect from observational data. It reduces selection bais from the two groups *Treatment* and *Control*.

Literature has shown that DID method has been used for panel data and short cutting of different interventions and programs. SCM has been used for intervention where there is no control group available to test, it also needs a huge data and many researchers have used it for time-series data. IV method can also be used for cross-sectional data but it runs on randomized control treatment. In last, RDD can also be used for cross-sectional data but it needs a range/limit for treatment like the PM laptop scheme in Pakistan has a range any student with a CGPA lower than 3.00/4.00 can't receive it.

CHAPTER NO 3
RESEARCH METHODOLOGY

3.1 DATA COLLECTION

The Household Integrated Economic Survey (HIES) data from the Pakistan Bureau of Statistics (PBS) website, for the year 2018-19 has been used in this study. The different rural areas of Pakistan with diverse population conditions have been used. Both microfinance clients' and non-clients data have been taken by the researcher. The HIES, Pakistan at the provincial level collects information from households about age, income, and expenditure as well as specific outcome indicators for education, health, population welfare, and housing (Statistics, June 2020). The financial and domestic economic activity for both groups, i.e. the treated group and the control group, will use the same procedure. This study assumes that households receiving small loans are considered the treatment group (TG) and control group (CG) who do not receive microloans from microfinance institutions.

The purpose of evaluating any project or activity, including microfinance, in order to understand both what happened and why it happened to the various participants. The method used by scientists to determine cause and effect is often experimental: applying a specific stimulus to a specific substance in a carefully controlled setting that excludes outside influences (Mosley, 1997).

The researcher adopted the econometrics method called Propensity Score Matching (PSM), a method to evaluate the effect of microfinance institutions on the poor’s well-being (where income expenditure, education expenditure, and food & non-food expenditure are used as a proxy for well-being), different researchers use different both psychological and sociological parameters for the wellbeing like life satisfaction, worthwhileness, happiness and anxiety used by (Daykin et al., 2017).

3.2 Propensity Score Matching Technique:

The “Propensity score matching (PSM)” technique has grown incredibly over the past decades. They are used primarily to match treatment and control units to estimate the causal treatment effect from observational studies or to link two or more data sets that share a common subset of covariates (Steiner & Cook, 2013).

In this approach, we no longer need to try to match each enrolled unit to a non-enrolled unit that has exactly the same value for all observed control characteristics. Instead, for each unit in the treatment group and in the pool of non-enrolled, we compute the probability that this unit will enroll in the program (the so-called propensity score) based on the observed values of its characteristics (the explanatory variables). This score is a real number between 0 and 1 that summarizes the influence of all of the observed characteristics on the likelihood of enrolling in the program Gertler et al. (2016).

The question about PSM arises how to compare groups that groups are not comparable?

Paul R Rosenbaum and Donald B Rubin first published the technique in 1983, and implement the "Rubin Causal Model" for observational studies. PSM is Quasi Randomized Experiment. Propensity Score Matching is the statistical analysis of observational data. By accounting for the covariates that predict receiving the treatment, it is the statistical matching techniques that aim to evaluate the effect of a treatment, policy, or other intervention. PSM seeks to minimize or reduce the biases caused by compounding variables that could be used to evaluate the treatment effect by comparing outcomes between units that received treatment and those that did not. We will make two groups of clients and non-clients for PSM and different matching criteria, we will find the best criteria for our study.

A comprehensive analysis using the most appropriate techniques is needed to learn lessons for appropriate policies. (Rosenbaum & Rubin, 1983) claim that by using propensity score matching and difference techniques to get beyond the selection bias and difference in observational characteristics, robust estimates can be obtained.

3.3 RESEARCH STRATEGY

Microfinance Institutions have different interventions like Asset transfer intervention, loan intervention, cash transfer intervention, etc. Various researchers try to evaluate these interventions for a different purposes. Loans from the World Bank to developing countries that offer microfinance fit into one of three categories of microfinance evaluation. **i**). Program Evaluation, **ii**). Product/Process Evaluation and **iii**). Policy Evaluation. Researchers use different techniques for these evaluations.

The study's primary goal is to check the well-being (parameters for well-being are Education Expenditure, Health Expenditure, and Food & Non-Food Expenditure) of poor people through the evaluation of microfinance in Pakistan (Harsha et al., 2016). The Impact evaluation is technique driven and methodology plays an essential role in these assessments.

Impact assessments can be performed to estimate the effects of the overall impact of a program or to evaluate the effect of a new product or policy. In both cases, the basic assessment question is the same: "How are participants' lives different from what they would be if the program, product, service, or policy were not implemented?" The question's first part is how are the participants' lives different. However, the second part requires measuring the counterfactual, or how those people's lives would have been different if the policy hadn't been implemented. This is the challenge of evaluation. An important difference between reliable and unreliable assessment is how well the design allows the researcher to measure the counterfactual. Policymakers usually review the impact of programs to decide how to deal with scarce resources. Though, the aim of most MFIs is the profit institutions that depend on private investment to support their activities/small business financially, while some institutions claim that evaluation is unjustified. At the same time, Microfinance institutions, like other businesses, usually focus on measuring program results. With this in mind, as long as clients pay off their debts and take out new loans, the program is supposed to meet the needs of the clients (Karlan & Goldberg, 2007)

3.4 RESEARCH DESIGN:

The following variables have been identified for the analysis:

Dependent Variable	Independent Variables
Household Well-being (HHW) (Where the parameters for HHW includes Education Expenditure, Health Expenditure, and Food & Non-Food Expenditure)	Province, Region, Household Age", Household Size", Education level, and Household Income

The initial stage of matching the proprietary score is to simulate the probability of becoming an MFI borrower. Only those variables that affect both the treatment group and the control group has been taken, and these are included in the Probit model from which we calculate the proprietary score. As a result, those variables which neither affect the treatment group nor the control group and only effect one of the mention groups have not been taken in this study.

3.5 SAMPLING

To address the objectives, this study has used Propensity Score Matching" (PSM) which is the best econometric technique for an observational and cross-sectional study. We also cheked the best matching criteria of "Propensity Score Matching" for the Evaluation of Microfinance.

Furthermore, different matching criteria have been tested of "Propensity Score Matching" (PSM) techniques for the best evaluation of MFI's intervention. The result of this method might slightly different from other methods like DID, RDD, Logit Model, and OLS etc. that other researches use these methods for impact assessment. After running the PSM econometrics technique we statistically test that our results are robust and we are not interested in result significance and reliability.

Once the data is available then the researcher will choose one of the best following "matching data techniques" of PSM and their effects on results and intervention:

- Nearest Neighbor Matching
- Radius Matching
- Kernal Method
- Stratification Method

3.6 ANALYSIS

This study aims to evaluate microfinance institutions in Pakistan based on Household Integrated Economic Survey (HIES) 2018-19 micro data from the Pakistan Bureau of Statistics (PBS).

Using Logistic (or Probit) regression to estimate:

Prob (T=1 | X1, X2, …, Xk) . . . (3.1)

The dependent variable is ***1*** if the group who got the treatment and ***0*** otherwise. In this case, Treatment (***T)*** is the dependent variable, and ***X1, X2, …, Xk*** are the independent variables.

$$DMFI = 1$$

"***D*** is a dummy variable that represents the "Treatment Variable" that indicates whether or not someone is borrowing money. (We have a dummy variable in our data that asks, "Have you or any member of your family borrowed?") and the answers were either yes or no, with borrowed=1 if anyone borrowed and 0 if no one borrowed.")

$$\delta_i = Y_{1i} - Y_{0i} \ . \ . \ . \qquad (3.2)$$

The impact of treatment for a participant denoted i, which is denoted by δ_i and $Y_{1i} - Y_{0i}$ showing a difference in possible outcomes in treatment and possible results in the control group (absence of treatment).

$$ATE = E(\delta) = E(Y_1 - Y_0) \ . \ . \ . \qquad (3.3)$$

Generally, an assessment seeks to estimate a program's average impact. in this equation ATE is showing the "Average Treatment Effect".

$$ATT = E(Y_1 - Y_0 \mid D = 1) \ . \ . \ . \qquad (3.4)$$

In this equation, the ATT shows the average treatment effect on the treated group. That measures the program's impact on individuals who participated.

$$ATU = E(Y_1 - Y_0 \mid D = 0) \ . \ . \ . \qquad (3.5)$$

In this equation, the average treatment effect on the untreated group is known as ATU. Which measures the program's impact on people who did not participate.

$$ATT = E(Y_1|D = 1) - E(Y_0|D = 1) \ldots \qquad (3.6)$$

The second term $(Y_0|D = 1)$ represents the average result that the treated members would have achieved in the absence of treatment, which is not observed.

$$\Delta = E(Y_1|D = 1) - E(Y_0|D = 0) \ldots \qquad (3.7)$$

Though, we do notice the expression (Y0 | D=0), which refers to the value of Y0 for untreated people (Sohag et al., 2015).

$$HHW = \beta 0 + \beta 1 HH_{Size} + \beta 2 HH_{Age} + \beta 3_{Province} + \beta 4_{Region} + \beta 5 HH_{Edu} + \beta 6 HH_{I} + \varepsilon$$

$$D_{MFI} = \beta 1 X1 + \beta 2 X2 \ldots \qquad (3.8)$$

Where province consists of four dummy variables, like *KP* = *pro1*, Punjab = *pro2*, Sind = *pro3*, and Balochistan *pro4*. Also made two dummies for a region like *Rural* = reg1 and Urban = *reg2*.

D_MFI is the dichotomous variable where D_MFI=1 means HH receives a loan, and 0 otherwise.

$$D_{MFI} = E(Y_1|D_{MFI} = 1) - E(Y_0|D_{MFI} = 1) \ldots \qquad (3.9)$$

(Siddiqui, 2013)

In the above equation (3.8) $\boldsymbol{HHW}$ shows the "HH Well-being" which is the dependent variable for analysis, which is an index of different indicators for example "Education Expenditure", Medical Expenditure, Food Expenditure and Non-Food Expenditure (Olubukunmi et al., 2015).

Whereas $\boldsymbol{b0}$ is an intercept, the rest of the variables are treated as independent variables such as $\boldsymbol{HH}size$ shows "Household Size", $\boldsymbol{HH}age$ shows "Household Age", *Region*, *Province*, $\boldsymbol{HH}edu$ shows "Household Education, $\boldsymbol{HHI}$ shows the "Income of a Household", and $\boldsymbol{\varepsilon}$ is an error term.

Many researchers are familiar with the statistics of planned experiments where a group randomly assigns the status of a treatment or control group. To evaluate the effects of treatments on outcomes, however, researchers frequently must rely on non-experimental, observational data. Like wellbeing, poverty, empowerment, health costs, etc. which are impossible or difficult to estimate in the artificial environment of a trial (Baser, 2006). That's the reason most researchers use propensity score matching for such kind of study.

CHAPTER NO 4

RESULTS AND ESTIMATIONS

In this section, we will talk about how to estimate the effect of a training program on the well-being of poor people in Pakistan. After balancing the differences in observable features, microcredit is found to be beneficial. The inference of households who have taken loans is estimated to have an average of (0.0105) higher well-being than those who have not taken microloans. On well-being, the Average Treatment Effect (ATE) has a positive and significant impact.

Why PSM instead of DID or any other Technique:

PSM (Propensity Score Matching) is a statistical method used to control for confounding variables in observational studies. PSM is particularly useful when there is a large number of potential confounders, and the sample size is relatively small. PSM is strongest when the following conditions are met: There is a strong likelihood that the treatment (or exposure) is related to the outcome of interest. There are many potential confounding variables that may affect the relationship between the treatment and outcome. The sample size is relatively small, and there is a concern that a simple comparison of treatment and control groups may be biased due to differences in confounding variables. The data are observational, and it is not possible to randomly assign participants to the treatment or control groups. In summary, PSM is strongest when there are many potential confounding variables, a small sample size, and the data are observational. It can be a valuable tool to estimate the causal effect of a treatment or exposure when a randomized controlled trial is not feasible or ethical.

Following are the reasons why we use PSM:

a. No other method is applicable

b. Assignment criteria is not given

c. A number of potential confounders

DID is one of robust quasi experimental method used to evaluate the causal impact of a program on the outcome of interest. Using DID requires two major assumptions i.e. 1) a parallel trend bef ore the exposure of the program and 2) strict exogeneity that means a sharp implementation of program, however, a continuous DID can relax the assumption of instance implemnentation of program and triple D can relax the assumption of parallel trend. But the program implementation is strictly required between two time spans.

By using observational data, the propensity-score matching technique (psmatch) calculates treatment effects. PSM uses an average of the results of similar subjects who receive the other treatment level to impute the missing potential outcome for each subject. The similarities between the subjects are based on the probability of the estimated treatment, called the proprietary score. The average treatment effect (ATE) is calculated by taking the average difference between the observed outcomes and potential outcomes for each participant. The teffects psmatch commands by default use propensity scores—estimated treatment probabilities—to calculate how close subjects are to one another. Propensity-score matching is the term for this kind of matching (STATA, 2018).

We will demonstrate how to apply teffects psmatch by using information from a study on the impact of micro-loan on poor households' well-being (HHW). This dataset also contains information about households in Pakistan i.e. *household age* (hh_age), *household education* level (hh_edu), *household income* (hh_I), and whether even their *Province* and *Region* have been also focused on. As the effects of maternal smoking status during pregnancy are measured using teffects psmatch (mbsmoke) on the baby's birth weight (bweight) reported by (Linden et al., 2020).

4.1 Summary Statistics:

Table 4. 1: Details of the Variables of Analysis

Variable Name	**Definition**
Wellbeing	Index variable of different indicators
TREAT	Treatment variable where treated=1 and 0 otherwise
pro1	Dummy for Khyber Pakhtunkhwa
Pro2	Dummy for Punjab
Pro3	Dummy for Sindh
Pro4	Dummy for Balochistan
reg1	Dummy for Rural region
reg2	Dummy variable for Urban region
hh_size	Size of the Household
hh_age	Age of the household head
hh_edu	Education of the household head
hh_income	Total income of a household last year

Table 4. 2: Distribution of Provinces by Region (%)

Province	Region		
	Rural	Urban	Overall
KP	2118	1078	3196
Punjab	5887	3013	8900
Sindh	2593	1993	4586
Balochistan	1309	628	1937
Overall	11907	6712	18619

Source: Author's Calculation

In Table 4.2 we have the observation of different provinces like KP, Punjab, Sindh, and Balochistan are 3196, 8900, 4586, and 1937 respectively.

Table 4. 3: Treatment and Control Group (Number of Participants)

	Freq.	Percent	Cum.
0	14586	78.34	78.34
1	4033	21.66	100.00
Overall	18619	100.00	

Source: Author's Calculation

In Table 4.3, we have 14,586 participants are in the control group who did not receive (microfinance loan) while 4,033 are in treatment group out of 18,619 observations.

Table 4. 4: Distribution of Treatment and Control Groups by Region (Number of Participants)

Urban	**Control**	**Treated**	**Total**
KP	528	550	1078
Punjab	2594	419	3013
Sindh	1754	239	1993
Balochistan	595	33	628
Total Urban	5471	1241	6712
Rural			
KP	956	1162	2118
Punjab	4666	1221	5887
Sindh	2261	332	2593
Balochistan	1232	77	1309
Total Rural	9115	2792	11907

Source: Author's Calculation

Table 4. 5: Mean Value of Output and Outcome Variables by Treatment (Number of Participants)

Variable	Full Sample	Treated	Control
wellbeing	-0.022	0.053	-.043
pro1	0.172	0.424	0.102
pro2	0.478	0.407	0.498
pro3	0.246	0.142	0.275
pro4	0.104	0.027	0.125
reg1	0.650	0.692	0.625
reg2	0.360	0.308	0.375
hh_size	6.344	6.801	6.217
hh_age	46.069	45.728	46.164
hh_edu	0.573	0.502	0.593
hh_income	132286.7	121807.67	135184.11

Source: Author's Calculation

If we look above Table, the average of hh_income is (135184.1) and (121807.7) in the case of TREAT=0 and TREAT=1 respectively. This shows that the treatment group who have received microfinance has a lower income than the control group. This difference tells that they are younger, less educated, have a high household size, and maybe few of them are married and have jobs.

It consists of Seven variables: an outcome is Household Wellbeing (HHW) which is y, a treatment indicator TREAT, and covariates are Province, Region, hh_age, hh_size, hh_edu, and hh_income. This is HIES data (2018-19) downloaded from the Pakistan Bureau of Statistics (PBS).

Table 4. 6: Mean Value of Output and Outcome Variables (Number of Participants)

Variable	Mean	Std. dev.	Min	Max	Label
wellbeing	-0.022	1.020923	-0.21	82.19	Scores for component 1
TREAT	0.2166067	0.4119434	0	1	Obs = 18619
pro2	0.4780063	0.4995295	0	1	Province = Punjab
pro3	0.2463075	0.43	0	1	Province = Sindh
pro4	0.1040335	0.31	0	1	Province = Balochistan
reg2	0.360	0.48	0	1	Region = urban
hh_size	6.344	3.21	1	55	
hh_age	46.069	13.85	16	99	
hh_edu	0.573	0.49	0	1	
hh_income	132286.7	180968.3	61200	9439000	

Source: Author's Calculation

In the above table after summarizing the mean value of TREAT is (0.217) which is 21% data for those who have received the treatment (i.e. Microfinance loan) and the mean value of well-being is (-0.022) which is the index variable of different indicators like health expenditure, education expenditure, food expenditure, and non-food expenditure.

Table 4. 7: Summary Statistics of Dependent and Independent Variables (Per year) by Treatment and Control Groups

TREAT = 0

Variable	Obs	Mean	SD	Min	Max
wellbeing	14,586	-0.043	1.030	-0.205	82.192
pro2	14,586	0.498	0.500	0	1
pro3	14,586	0.275	0.447	0	1
pro4	14,586	0.125	0.331	0	1
reg2	14,586	0.375	0.484	0	1
hh_age	14,586	46.164	13.961	16	99
hh_size	14,586	6.217	3.171	1	36
hh_edu	14,586	0.593	0.491	0	1
hh_income	14,586	135184.1	188629.4	61800	9439000

TREAT = 1

	Obs	Mean	SD	Min	Max
wellbeing	4033	.053	.984	-.205	24.514
pro2	4033	.407	.491	0	1
pro3	4033	.142	.349	0	1
pro4	4033	.027	.163	0	1
reg2	4033	.308	.462	0	1
hh age	4033	45.728	13.433	16	90
hh size	4033	6.801	3.304	1	55
hh edu	4033	.502	.5	0	1
hh income	4033	121807.7	149582.6	61200	6219400

Source: Author's Calculation

Dummy for province and region:

As we had KP=1, Punjab=2, Sindh=3, and Balochistan=4 in HIES data. We finally made 4 dummies for provinces like *KP* as a base categorical variable which is *pro1* and the rest 3 dummy for other provinces for example *pro2* for Punjab, *pro3* for Sindh, and *pro4* for Balochistan. Also made a dummy for a region like *Rural* as a base category which is *reg1* and *reg2* for *Urban*.

Table 4. 8: Regression with a dummy variable for treatment controlling for x

wellbeing	**Coef.**	**SE**	**t-value**	**p-value**	**[95% Conf**	**Interval]**
TREAT	0.072	.02	3.70	0	.034	.111
pro2	-0.094	.022	-4.21	0	-.138	-.05
pro3	-0.084	.025	-3.34	.001	-.133	-.035
pro4	-0.119	.031	-3.85	0	-.182	-.06
reg2	0.038	.016	2.39	.02	.005	.068
hh_age	0.004	.001	7.92	0	.003	.006
hh_size	0.011	.002	4.36	0	.006	.016
hh_edu	0.062	.016	3.91	0	.031	.092
hh_income	2.107	.027	9.15	0	.014	.071
Constant	-0.332	.038	-8.66	0	-.408	-.257

Mean dependent var	-0.022	SD dependent var	1.021
R-squared	0.016	Number of obs	18619
F-test	32.555	Prob > F	0.000
Akaike crit. (AIC)	53337.658	Bayesian crit. (BIC)	53415.977

**** p<0.01, ** p<0.05, * p<0.1*

Source: Author's Calculation

Greater well-being is correlated with higher income, although income level changes effects wellbeing differently. Using subjective-well-being data from Germany and the United Kingdom, the study found that losses in income have a larger effect on well-being, this effect is explained by diminishing income to well-being (Boyce et al., 2013).

Our results show that the covariates like “household age”, “household size”, “household education” and “household income” positively correlated with the dependent variable “household wellbeing”. Highly significant “household Income” has a greater effect on well-being with a coefficient value of 2.107, the increase of one unit change in *HHI* will effect *HHW* by 2.107 units. This means if there will one unit change occurs in household income that will not increase household wellbeing.

“household age” will bring a 0.004 unit change in the well-being of poor people, an increase of one unit in “household size” will bring a 0.011 unit change in well-being, and one unit change in “household education” will increase 0.062 unit change in wellbeing.

The coefficient value of the TREAT variable got lower if we are controlling for independent variables. In this case, the coefficient value for TREAT shows *wellbeing* will be increased by 0.072 units, if we increase one unit in TREAT, that means the treatment group higher the *wellbeing* by 0.072 units than the control group.

The Effect of microfinance on household wellbeing in Punjab, Sindh, and Balochistan has less effect by (-0.094), (-0.084), and (-0.119) coefficient values than KP (0.121) respectively.

Table 4. 9: Coefficient Values of Variables at Different Stages

Variables	Simple Regression	PSM	PSM Logit	Before Matching	After Matching	Difference
TREAT	0.072	0.053	0.053	0.053	.077	0.024
pro2	-0.094	-0.960	-1.586	-1.586	-.027	1.559
pro3	-0.084	-1.248	-2.116	-2.116	-.039	2.077
pro4	-0.119	-1.780	-3.158	-3.158	.119	3.277
reg2	0.038	-0.105	-0.191	-0.191	.031	0.222
hh_age	0.004	-0.008	-0.013	-0.013	.006	0.019
hh_size	0.011	0.028	0.049	0.049	.014	-0.035
hh_edu	0.062	-0.260	-0.458	-0.458	.172	0.63
hh_income	2.107	1.331	1.237	2.006	2.117	0.111
_cons	-.332	0.479	0.849	0.849	-.456	-1.305

Source: Author's Calculation

The Difference has been shown in the table for example in the case of "household income" the effect has increased by **0**.111 as it was (2.006 before matching and 2.117 after matching and the "household age" effect has increased by 0.019 and so on.

4.2 Propensity Score Matching:

PSM is a method that can be used when no other quasi experimental method is valid, for instance, when the assignment criteria is not given then the matching on the demographic and geographic characteristics scores can be fruitful.

Our estimator is "Propensity Score Matching" Where TREAT is the treatment variable and the rest are the covariates or independent variables that include province, region, household's age, size, education, and income. In the propensity score matching, we will not give a command of the outcome variable which is household ***wellbeing***.

myscore = variable which store the propensity score that we would match in later steps myblock = here we are collecting a block id which represents the number of blocks that the program will be determining optimum. Within these blocks, we would have observations with similar X-characteristics.
comsup = this is called common support, this is because We just want to compare the observations that they have a similar propensity score in the same range.

Table 4. 10: Propensity Score Matching with Common Support

TREAT	**Coeff**	**Std. err.**	**ATT**	**P>z**	**[95% conf.**	**interval]**
pro2	-0.960	0.028	-34.430	0.000	-1.014	-0.905
pro3	-1.248	0.033	-37.460	0.000	-1.313	-1.182
pro4	-1.780	0.052	-34.190	0.000	-1.882	-1.676
reg2	-0.105	0.024	-4.420	0.000	-0.150	-0.056
hh_age	-0.008	0.001	-9.050	0.000	-0.009	-0.006

hh_size	0.028	0.004	7.620	0.000	0.020	0.035
hh_edu	-0.260	0.023	-11.260	0.000	-0.305	-0.215
hh_income	1.331	0.050	9.430	0.000	0.027	0.062
_cons	0.479	0.052	9.200	0.000	0.377	0.581

Variable	**Sample**	**Treated**	**Controls**	**Difference**	**S.E.**	**T-Stat**
Wellbeing	**Unmatched**	0.053	-0.043	0.095	0.018	5.250
	ATT	0.053	0.001	0.052	0.048	1.080
S.E. ignores and does not take into account that the propensity scores are estimated						

Source: Author's Calculation

HHW is Household Wellbeing which is the dependent variable, a treatment indicator TREAT, the rest variables are *Province*, *Region*, *hh_age*, *hh_size*, *hh_edu*, and *hh_income*.

ATT is actual concern with the treated group (4,033) not a control group (14,586) of our sample. The coefficient value of ATT shows that if the treared group receive the treatment that will effect household's wellbeing with mentioned coefficient values. On the other hand, ATE is the total sample of the study which is 18,619 out of this 14,586 are controlled and 4,033 are treated observation. AT shows the difference between treated and control groups.

The treatment effect is a one-unit increase in the dependent variable and its probability is correlated positively with X-list. hh_size is also positively correlated; the rest of the covariates have a negative correlation with the dependent variable. As a result, comparing the mean value of the dependent variable for both treated and untreated groups poorly overvalues the effect of treatment.

This is the [1]Propensity Score Model with Probit regression which is the same as the probit Model. We have higher ages, more education, and household with the high income are less likely to have received the treatment.

Table 4. 11: Estimated Propensity Score

	Percentiles	**Smallest**	
1%	.0320515	.0042912	Obs 18,617
5%	.0522285	.009093	Sum of weigt. 18,617
10%	.0734675	.0139163	Mean .217
25%	.1158595	.0139945	Std.dev .159
50%	.1673141	**Largest**	Variance .025
75%	.2390621	.7595687	Skewness 1.407
90%	.5200601	.7658265	Kurtosis 3.913
95%	.5792245	.825186	
99%	.6495823	.8256715	

[1] Note: common support option has been selected the region of common support and we do have a propensity score [.00326043, .82162473] which does not reach and highest than 1. Simply, we do not have a propensity score above 0.8. (We will put this 0.8 as a radius number in Radius Matching command).

4.2.1 Optimal Number of Blocks Identification

The final number of blocks is 18. This number of blocks ensures that the average propensity score for treatment and control is not different in each block. So that's a good thing.

4.2.2 Test of propensity score's balancing property

In block 8, variable pro2 is poorly balanced

In block 8, variable pro3 is poorly balanced

In block 9, variable reg2 is poorly balanced

In block 8, variable hh_edu is poorly balanced

The balancing property has been satisfied: that means in each of these blocks in the following tables that we have only a propensity score is similar in x characteristics which we match are also similar.

Table 4. 12: Blocks Distribution of both the Number of Control and Number of Treated

Inferior of block of pscore	**TREAT**		
	0	**1**	**Total**
0	50	1	51
0.025	312	13	325
0.037	441	35	476
.05	1,042	64	1,106
0.075	1,431	146	1,577
.1	3,532	518	4,050
.15	2,097	378	2,475
0.175	1,047	199	1246
0.1875	798	218	1016
.2	1,524	443	1,967

.25	786	287	1,073
.3	128	55	183
.4	170	97	267
.45	319	292	611
.5	422	447	869
.55	258	378	636
.6	227	460	687
.8	0	2	2
Total	**14,584**	**4,033**	**18,617**

Note: The option for common support has been chosen.

Calculating Propensity Score:

We can get from these propensity score models to estimate the predicted probability or propensity score on which we will be matching later in "matching methods".

myscore column in the data shows the propensity-score/ likelihood for all the households has received the treatment and the highest p-score is 0.8 in our case which we received from the program. While myblock shows which of the 08 Blocks that myscore observation belongs to. Finally, comsup tell us the common support is 1 to all of them because we use it from the option.

4.3 Matching Methods:

The variables that we used to match are *Province*, *Region*, *Household Age*", *Household Size*", *Education level*, and *Household Income*. To reduce group selection bias in observational data, propensity score estimation is essential in PSM. We have created a bootstrap propensity score to increase the accuracy of propensity score estimation. When evaluating the quality of bias reduction results using common propensity score matching techniques such as nearest neighbor matching, radius matching, kernel matching, and stratification matching calculated propensity scores with bootstrap. The important thing is that PSM has not the dependent variable in command, as other matching methods have it.

4.3.1 Nearest Neighbor Matching Criteria:

When estimating treatment responses from observational data, nearest neighbor (NN) propensity score (PS) matching technologies are commonly used. PS matching is rarely used along with bootstrapping, which is frequent use to correctly estimate variance (Geldof et al., 2020). On a household dataset with differing levels of socioeconomic complexity, we looked at the performance of bootstrapping combined with PS matching against several NN matching techniques. According to (Bai, 2013) the results of matching using bootstrap propensity scores are higher than or comparable with those without bootstrap procedures.

Table 4. 13: Nearest Neighbor Matching Values

treat	**contr**	**ATT**	**SE**	**t**
4033	5488	0.059	0.027	2.128

After bootstrapping the rest observation will remain same but the standard error (SE) will increase or decrease, here in our case the SE has increased from 0.029 to 0.042.

The number of matches per observation is specified by the nneighbor (#). neighbor is used by default (1). Every individual is paired with at least the specified number of individuals from the other treatment level. nneighbour () must be a number greater than or equal to 1, but not greater than the number of observations in the smallest group.

4.3.2 Radius Matching Criteria:

We consider two choices for the radius matching 0.1 (as a default) and 0.8 (which we get after running the proprietary score matching). In one-to-one (or pair) matching, the radius is adjusted as a function of the distances between matched treated and controls.

Table 4. 14: Radius Matching Values

radius	treat	contr	ATT	SE	t
0.1	4033	14584	0.106	0.016	6.543
0.8	4033	14584	0.095	0.017	5.587

After giving the radius command with 0.8, the number of treated and controls are equal in both radius values 0.1 and 0.8. There is a slight change as ATT has come down from 0.106 to 0.095. The standard error is approximately equal and both are significant at level 1%.

4.3.3 Kernel Matching Criteria:

Table 4. 15: Kernel Matching Values

treat	contr	ATT	SE	t
4033	14584	0.063	0.015	4.250

Kernel matching appeared to produce results similar to nearest neighbour matching. Only a few observations from the comparison group are needed to create the counterfactual outcome of a treated individual in all of the matching algorithms that have been mentioned so far. Kernel matching (KM) is a non-parametric matching estimator that creates the counterfactual result using weighted averages of each member of the control group (Caliendo & Kopeinig, 2008).

4.3.4 Stratification Matching Criteria:

Table 4. 16: Stratification Matching Values

treat	contr	ATT	SE	t
4033	14586	0.062	0.014	4.320

It appeared that stratification matching was similar to nearest neighbour and kernel matching and their effects on wellbeing is also similar. If we suspect unobservable effects in the matching, the stratification method is extremely useful. Because stratification groups similar observations, it is believed that the effects of unobservable will become less significant and diminish (Baser, 2006)(Baser, 2006).

Table 4. 17: Different Matching Criteria's Output:

Matching Types	treat	contr	ATT (Difference)	SE	t-value
Unmatched	4033	14,586	0.095	0.018	5.250
Nearest Neighbor	4033	5488	0.059	0.027	2.128
Radius (0.1)	4033	14,584	0.106	0.016	6.543
Radius (0.8)	4033	14,584	0.095	0.017	5.587
Kernel	4033	14,584	0.063	0.015	4.250

Stratification	4033	14,586	0.062	0.014	4.320

Source: Author’s Calculation

We have an Average Treatment effect on Treated (ATT) matching criteria, *n.treat.* value shows number of treated groups and *n.contr.* shows number of control groups that controlled different matching criteria. ATT value is the difference between the outcome of these *n.treat.* value and outcome of n*.contr.* value after matching. This is the effect we can say that if someone or some household has taken the program their *wellbeing* will increase with *ATT* units which benefits their well-being by different percentages (STATA, 2018).

Statistics are constant across the table except for the radius matching. The ATT value for the nearest neighbor is 0.059 which represents that if someone or some household has taken the program their *wellbeing* will increase by 0.05 units which are benefiting their well-being by a lower percentage. The values of nearest neighbor, kernel, and stratification criteria are almost similar.

The correct matching procedure provides the estimate closest to its regression counterpart. The best matching criteria are Radius matching having (0.1) estimated the treatment effect as 0.106 and radius matching (0.8) estimated the treatment effect, it becomes decreases to 0.95. Which is similar to the unmatched difference, which is still higher than rest three criteria. That's double the amount obtained by the wrongly chosen method of the nearest neighbor. The difference is significant in practice and statistically. From that, we conclude the best criteria is “radius matching criteria” in our case.

4.4 Regression after Matching:

a). Average Treatment Effect: (Logit)

Table 4. 18: Logit Values: Average Treatment Effect

Wellbeing	Coef.	SE	t-value	p-value	[95% Conf	Interval]	Sig
ATE TREAT (1 vs 0)	.0105	.034	3.06	.002	.038	.172	***
Mean dependent var	-0.022	SD dependent var	1.021				
**** p<.01, ** p<.05, * p<.1*							

The treatment Model is Logit and has been estimated using (18,619) observations. Average Treatment Effect (ATE) in population in this case. The inference of household who has taken loan was on average (0.0105) higher than the inference of households who did not take a microloan. ATE has a positive and significant impact on wellbeing by looking at the T-Statistics [3.06] and P-Statistics (0.002). That means if 1 unit change in ATE will effect (increase) wellbeing by 0.01 units).

b). Average Treatment Effect on Treated Group:

Table 4. 19: Logit Values: Average Treatment Effect on Treated

Wellbeing	Coef.	SE	t-value	p-value	[95% Conf	Interval]	Sig
ATET TREAT (1 vs 0)	.051	.026	1.98	.048	0	.102	**
Mean dependent var	-0.022	SD dependent var	1.021				
**** p<.01, ** p<.05, * p<.1*							

When we repeat the same calculation for the Average Treatment Effect for the Treated (ATET), the output is almost the same as ATE with the coefficient value of (0 .0644904).

c). Average Treatment effect on Treated Group: (Probit)

Table 4. 20: Probit Values: Average Treatment Effect

Wellbeing	**Coef.**	**SE**	**t-value**	**p-value**	**[95% Conf**	**Interval]**	**Sig**
ATET TREAT (1 vs 0)	.059	.028 1428	2.90	.036	.004	.114	***
Mean dependent var		-0.022	SD dependent var				1.021
*** *p<.01*, ** *p<.05*, * *p<.1*							

Table 4. 21: Propensity Score for Average Treatment Effect using logit:

Variable	Sample	Treated	Controls	Difference	SE	T-stat
Wellbeing	**Unmatched**	0.053	-0.043	0.095	0.018	5.250
	ATT	0.053	0.004	0.049	0.037	1.330
	ATU	-0.043	0.097	0.139	.	.
	ATE			0.120	.	.

The ATT/ATET from the previous model and the ATE from this model are extremely similiar. But take note that in this model, psmatch2 is reporting a slightly different ATT. If prompted, the teffects command returns the same ATET. The difference between the Average Treatment Effect on Treated Group (ATT/ATET) is lower than the Average Treatment Effect on the Untreated Group (ATU) and Average Treatment Effect (ATE).

Table 4. 22: Treatment Effects by Propensity Score Match for ATET:

Wellbeing	Coef.	SE	p_value	p_value	[95% Conf	Interval]	Sig
ATET TREAT (1 vs 0)	0.049	.026	1.98	.048	0	.102	**
Mean dependent var	-0.022	SD dependent var	1.021				
*** *p<.01*, ** *p<.05*, * *p<.1*							

When propensity scores are estimated SE is not taken into account. A recent paper (Abadie & Imbens, 2012) determined how to estimate propensity scores. effect psmatch depends on their work. Interestingly, adjustments for ATE are always negative, leading to smaller standard errors: matching based on estimated propensity scores is more effective than matching based on real trend scores. Though, adjustments for ATET can be positive or negative, so the standard errors reported by psmatch2 can be too large or too small.

So far, we have done straightforward nearest-neighbor matching with a single neighbor using psmatch2 and teffects psmatch. However, this creates the issue of what to do when two observations are tied for "nearest neighbor" because they have the same propensity score. If the covariates in the treatment model are categories or even integers, ties are frequently seen. The psmatch2 command matches with all tied observations instead of just one of the tied observations by default. The psmatch command from teffects always matches with ties. We won't obtain the same results from teffects psmatch as you were receiving from psmatch2 if our data set has several observations with the same propensity score unless we go back and add the ties option to our psmatch2 commands. At the moment, we are not aware of any definitive rules stating whether or not it is preferable to match with ties.

4.5 Matching with Multiple Neighbors:

For instance, we could, compare and match each observation to its three closest neighbors. Every observation is matched with one other observation using teffects psmatch by default. With the nneighbor() (or just nn()) option, we can change this.

Table 4. 23: Matching with Multiple Neighbors and Treatment Effect with PSM

Wellbeing	**Coef**	**SE**	**t_value**	**p_value**	**[95% Conf**	**Interval]**	**Sig**
ATE TREAT (1 vs 0)	.105	.034	3.13	.002	.039	.171	***
r1vs0	.105	.034	3.13	.002	.039	.171	***
Mean dependent var	-0.022			SD dependent var	1.021		
**** p<.01, ** p<.05, * p<.1*							

4.6 Post Estimation:

Table 4. 24: Post Estimation

Obs	**TREAT**	**Wellbeing-B**	**Wellbeing-A**	**pscore**	**weight**	**match1**	**ps0**	**ps1**	**y0**	**y1**	**te**
1	0	-0.199	-0.205	0.165	5	15466	0.835	0.165	-0.198	-0.188	0.009
15466	1	-0.205	-0.198	0.165	19	1	0.835	0.165	-0.190	-0.204	-0.014

Finally, we get the output of all observations (both treated and control group) we realize that the highest *match* number is 21 which mean some of the observation has been matched with 21 other observations. Both *wellbeing* before and *wellbeing* after matching values *pscore* which is the propensity score of the observation have been given. *weight* value is showing that how many observations are matched with base observation. The probability of being in the control group is represented by ps0, whereas the probability of being in the treated group is represented by ps1.

If we look at the above table, the first observation is from the controlled group and matched with the 15466th observation which is from the treated group. The first observation having Propensity Score Zero (*PS0*) is (0.165) which means their well-being will be increased by 0.165 units if they will receive treatment and 0.835 units otherwise.

When using teffects psmatch the data set is not expanded with any new variables by default. However, options and post-estimation predict commands can be used to create a wide range of useful variables. After some of these variables have been established, the first and 15,466th observations of the example data set are listed in the above table. As we describe the commands that produced the new variables, we'll refer to them. Reviewing these factors might also help you ensure that you understand fully how propensity score matching works.

Since there is only one match between each observation, in this case, the gen(match) command only generates match1. According to the example output, observation 1 and observation 15,466 are listed since they match.

Teffects psmatch is instructed to generate a new variable (or variables) by the gen() option. The number of observations that each observation was matched with will be stored in this new variable for each observation. Some variables will need to be created by gen() if there are ties or if you instructed teffects psmatch to use more than one neighbour. As a result, you only need to specify the variable name's stem; teffects psmatch will append suffixes as necessary.

Note: We are matching each observation after looking *match1* column as their _pscore is almost the same as the match observation and the base observation's *_id* is the same as matched observation's *_n1* value.

Predicting ps0 ps1, ps:

The propensity scores, or the predicted probability that an observation will belong to either the control group or the treated group, are created in two variables by the predict command with the ps option:

Here, the expected probabilities of being in the control group (TREAT=0) and the treated group (TREAT=1) are represented by ps0 and ps1, respectively. Because of the striking similarity in their propensity ratings, observations 1 and 15,466 were matched.

Predicting y0 y1, po:

Each observation's possible outcomes are created as variables by the po option:

Since observation 1 is a member of the control group, y0 includes the observed value of wellbeing. y 1 represents the wellbeing value that was noticed for observation 1's match (observation 15,466). The propensity score matching estimator assumes that observation 1's value of wellbeing would have been that of the observation in the treated group that was similar to it in terms of characteristics (where "similarity" is measured by the difference in their propensity scores).

Observation 15,466 belongs to the treatment group, therefore its value for y1 is the observed value of y, and its value for y0 is the observed value of y for observation 1, which is its match.

Predicting te:

Running the predict command without any options provides the same result as the treatment:

The difference between y1 and y0 represents the treatment effect.te = y1 - y0

Summary of Treatment Effect

Variable	Obs	Mean	Std. dev.	Min	Max
te	18619	.1046 38	1.527169	-80.64952	24.71893

We could calculate the ATE (but emphatically not its standard error)

Summary of Treatment Effect by Treatment:

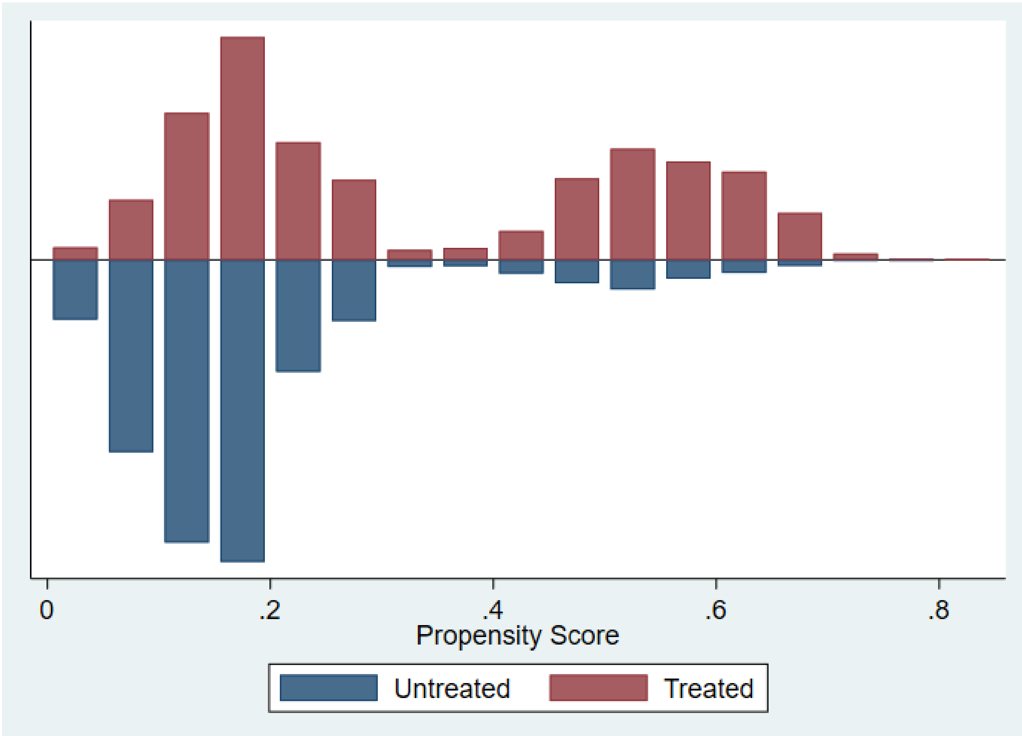
ATET with this command

Variable	Obs	Mean	SE	Min	Max
te	4,033	.051193	1.441942	-48.52044	23.89493

The basic criterion for this approach is to delete all observations whose propensity score is smaller than the minimum score and larger than the maximum in the opposing group. For the sake of example, let's say that the propensity score falls between [0.07, 0.94] and [0.04, 0.89] for the treatment group and control group, respectively. As a result, using the "minima and maxima criterion," [0.07, 0.89] provides common support. Outside of this range, observations will not be included in the analysis (Caliendo & Kopeinig, 2005).

4.7 Treated and Untreated Propensity Scores:

Figure 4. 1: Treated and Untreated Propensity Score (PSgraph)



In this graph, we see that individuals in the blue were untreated and individuals in red were treated, as previously indicated by psmatch output. Some evidence of overlap in the propensity score of the household is shown. As we can see in some place there is a lot of untreated observation that are matched with few treated observations on the other hand very few households' observation is matched with many treated households. Because we are comparing households in HIES having the same characteristics.

The PSM does provide some households which have similar characteristics i.e. high dependency, poor education, worse medical condition, low food, and other expenditure, etc. Two groups (having the same demography in past can't be similar in the future cause of state change. We have to be clear conceptually.

CHAPTER NO 5

LOCALE

Before choosing the topic, I have taken interviews with different microfinance clients and non-clients of different regions in Pakistan i.e. Parachinar (different villages), Peshawar (University road, Tahkal, and Qisakhwani), Taxila (Nawababad and Chachi Mohala), Wah Cantt (Aslam Market) and Islamabad (Bhara Kahu).

I found that most of the loan has been used for other activities like purchasing a cell phone, construction, wedding, and different functions instead of SMEs and income-generating activities. This is also helping the well-being of the poor in another way like they also have to do these activities. Some of them told that due to collateral requirements, interest rates, and the installment return system, most people are stuck in debt and there is no easy way to out of this debt web easily. Some of them are taking a loan from a new source and paying to old institutions. Getting assistance from microfinance institutions is putting them a burden instead of eradicating poverty and making a healthy and high quality of life.

Then I visited different microfinance institutions and like Khushali Bank, NRSP, UBank, Kashaf, SRSP, and the commercial bank that provides small and medium loans like HBL, etc., and ask different questions[2] and they respond that most of the loan is available for female/women empowerment and loan will be provided on group bases. Installments will be on monthly basis with a 3-8 % of interest rate and student and government employees can't get a loan. The owner

[2] What is the loan limit that you are providing?
What is the interest rate on providing the loan?
Return period
Can a person take a loan after getting a loan from another MFI?
Can one take a loan on an individual basis?

of their house will provide a guarantee if the receivers do not have their own house. The loan will not provide to one who is already taking a loan from other microfinance institutions, as this is a good step because it will keep all the participants safe from being stuck in the loan web.

CHAPTER NO 6

CONCLUSION & RECOMMENDATION

This study outlines the benefits of microfinance institutions in terms of income-generating opportunities, expenditure of education, health & food expenditure, growth, and poverty.

MFIs aim to focus on poor families who have little or no access to credit to set up small businesses, The major finding of this study is that microfinance has significant impact on well-being of poor people all over Pakistan, especially in rural areas which is indirectly helps growth of the country.

Microfinance Institutions have always lifted the poor out of extreme poverty and increasing employment rate that will bring the poor out of extreme poverty like expenditure for education, health expenditure. and especially women empowerment etc.

Providing micro-credit to undergraduate and bachelor students, as they will start a small business that will help them pay their academic fees, hostel charges, market experience, save for future studies, and reduce the fee burden on their families.

Micro credits with a low-interest rate or even zero interest rate along with providing different ideas to the poor about Small and Medium Enterprises (SMEs).

More demographic and economic information about households is needed for further analysis like income-generating activities, how much they earn from that small businesses

Initiate and launch sessions of training to understand the loaner with proper information of efficiently governing their small enterprise and assist in everyday life.

Credit groups (an effective management tool) that enforce clients for repayment system and also check their repayment mechanism.

The clients of MFIs have to join mobilization programs of savings that need loaners to create a saving account and gather financial resources. Among such characteristics, group meetings and training are also necessary tools for microcredit programs.

MFI borrowers needs to take part in the capacity development programs and attend all MFI activities like risk management and entrepreneurship skills, credit discipline, values creation, and knowledge on hygiene and health, among others.

The Government has to inform all the citizens through different programs about MFIs as it is a good source for SMEs like village shops, vendors, sewing machines for women, beauty parlors.

Microfinance must be included in overall development planning because of its numerous effects. This study analyzes the impact of microfinance institutions using propensity score matching and different matching methods to the literature on microfinance in Pakistan.

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