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Absolute Poverty and Microfinance: A Critical Appraisal of Rural Households in Chakwal, Punjab

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ABSTRACT

Despite the widening of microfinance in Pakistan, poverty alleviation and sustainable development remain unachieved, particularly in rural areas where the lower middle class is moving towards extreme poverty. Poverty alleviation was a key goal of the Millennium Development Goals (MDGs), but the rural population faces socioeconomic marginalization and limited access to necessities and financial services. Resilient and smooth financial linkages between local communities, farmers, and small business entities, combined with private and public financial organizations, are crucial for poverty alleviation. The micro financial sector has been declining in Pakistan for the last four decades, with the majority of rural populations living below the poverty line, especially in rural areas of Punjab, having limited access to financial and banking operations. This study aimed to explore whether microfinance is truly eliminating poverty in rural areas of Punjab, Pakistan. The research used the Before and After approach, Foster, Greer & Thorbecke class of poverty measures, and Alkire et al. (2011) methodology to assess the impact of financial appropriation on living standards and decline of economic poverty, absolute poverty. The results showed a positive interaction between broad finance and living standards, a negative association between financial invasion and socioeconomic catastrophe hazards in rural areas of Punjab like district Chakwal, Pakistan. Financial inclusion was found to be a probable determinant of economic poverty reduction, and the agriculture sector had the upper hand compared to other sectors. These findings can help policymakers and stakeholders understand the dynamics of socioeconomic adversity and the function of financial addition in achieving realistic socioeconomic uplift programs in rural Punjab.

Introduction

According to the 2020 Global Human Development Report, between 119 and 124 million people live in poverty throughout the world, illustrating the issue's persistence and complexity. Despite progress in tackling poverty, it remains a difficult issue that requires reforms in financial institutions and poverty-fighting methods at both the local and international levels. The capacity approach, the monetary approach, and the social exclusion approach are the three major techniques for analyzing and assessing poverty. Poverty is defined as the deprivation of possibilities, the erosion of human dignity, and the absence of fundamental resources required for societal engagement. This encompasses limited access to food, clothes, education, healthcare, and financial services, resulting in emotions of powerlessness and marginalization. The monetary method evaluates poverty mostly by income levels, determining whether people possess enough resources to satisfy fundamental necessities. This technique has drawbacks, especially in delineating what defines a core income level (Ameer et al., 2024; Asghar et al., 2024).

The poverty line may be evaluated using two primary frameworks: relative and absolute measures. The absolute poverty method encounters difficulties owing to diverse financial, cultural, and resource conditions in many cultures. To rectify these differences, it is recommended that absolute poverty levels be determined at the national level. In contrast, the relative poverty method sets criteria according to community income levels and the cost of vital items, emphasizing living standards and the capacity to get essentials. This strategy may not successfully reduce poverty owing to intrinsic biases in resource allocation. Monetary poverty is affected by economic factors and nutritional requirements, with variations in costs and availability hindering access to vital supplies. A more complex technique entails defining poverty using income brackets, categorizing persons whose earnings fall below a certain level as destitute. Economists often analyze poverty via an individual welfare lens; however, data gathering at the household level may provide a more precise calibration of poverty thresholds.

The capacity approach redirects attention from money to human development, highlighting well-being as a more dependable indicator for evaluating poverty (Taqi et al., 2021; Munir et al., 2022). This method acknowledges the intricacy of economic systems and the volatility of financial resources, indicating that monetary indicators may not consistently represent an individual's potential for advancement. The capacity method also takes into account aspects such as gender, age, and social integration when establishing poverty levels, with the objective of improving total wellbeing. Social exclusion, especially in developed countries, refers to the marginalization that transpires when people or groups are partly or wholly disengaged from society. Factors leading to social isolation include inadequate income, unemployment, and restricted access to housing and social entitlements. Setting standards for developing economies is difficult since significant social interactions often fail to tackle underlying problems such as class systems and unemployment.

To evaluate social justice, it may be advantageous to use standards from other nations, established via collaborative procedures rather than individual attributes. This methodology may assist in identifying disadvantaged persons and groups while aligning with other poverty evaluation techniques. Social exclusion may result in the formation of a social underclass and societal fragmentation, highlighting the need to tackle distributional disparities and guarantee the participation of all society groups. Microcredit developed as a significant tool for poverty reduction, earning attention since its establishment in Latin America in 1986. Muhammad Yunus and the Grameen Bank were awarded the Nobel Peace Prize in 2006 for their foundational contributions to socio-economic development. The worldwide microfinance sector is valued at over $124 billion, catering to approximately 211 million consumers as of 2015. Nonetheless, extending credit to microfinance institutions (MFIs) entails risks associated with moral hazards and adverse selection, typically resulting from insufficient collateral.

Microfinance institutions have devised novel techniques to alleviate these risks, including shared responsibility and dynamic incentives. Grameen Bank had remarkable payback rates ranging from 96% to 100% in the late 1990s. Recent studies suggest a decrease in the efficacy of shared liability loans, with success increasingly ascribed to alternative lending technologies and dynamic incentive schemes. As competition in the microfinance business escalates, MFIs have difficulties in sustaining elevated payback rates due to concurrent borrowing and deliberate defaults. The proliferation of for-profit entities in the microfinance industry may be ascribed to two primary factors: the prior success of microfinance institutions (MFIs), which drew new participants pursuing profit, and the transition from dependence on donor financing as MFIs evolved. This transition has resulted in market saturation, when profit-driven objectives may eclipse the initial social goal of microfinance institutions. Non-profit microfinance institutions stress borrower welfare, while for-profit organizations emphasize financial returns, resulting in a confluence of interests in several institutions.

The empirical data about the objectives of microfinance institutions is inconclusive, with some research indicating that profit maximization may coexist alongside poverty reduction initiatives. The two principal methodologies of microfinance—poverty alleviation and financial system approaches—remain subjects of contention, both presenting distinct viewpoints on microfinance's function in combating poverty. Poverty's multidimensional character necessitates a thorough comprehension of its many facets, including economic, societal, and human elements. The strategies for evaluating poverty, including the monetary, capability, and social exclusion approaches, provide significant insights into the intricacies of poverty reduction. The evolution of microfinance as a tool for poverty reduction highlights both the potential benefits and challenges associated with financial interventions in impoverished communities. Addressing poverty effectively necessitates a collaborative and nuanced approach that considers the diverse experiences and needs of individuals and communities.

Table 1: Microfinance approaches poverty reduction versus financial system

	Poverty Reduction	**Financial System**
Problem definition	Reduction in market imperfection	Decrease uncertainty transaction costs
Role of financial market	Help the poor, promote techno stimulate production, and implen state plans	Use resources more efficiently
View of users	Borrowers and beneficiaries selected as targeting	Borrowers and depositors as cli choosing products
Subsidies	Large subsidies	No or little subsidies
Sources of funds	Governments	Most are voluntary deposits
Associated informa systems	Designed for donors	Designed to monitor manager activities
Sustainability	Largely ignored	A major concern
Evaluations	Credit impact on beneficiaries	Performance of finar institutions

Source authors constructions

The study aims to assess the impact of competition and mission drift on lenders' optimum contracts when using dynamic incentives for repayment. It is crucial to analyse this as competition can negatively affect a bank's capacity to collect repayments. If lenders deny defaulters access to future loans, this can increase financial exclusion of the disadvantaged. A profit motive scheme requires banks to be tighter when seeking payment, leading to more exclusion and ultimately rendering the system unsustainable. The study aims to determine how microfinance institutions can assure repayment from borrowers through other mechanisms, the advantages of dynamic rewards over alternatives, definitive loan agreements for lenders applying dynamic incentives, and the reduction of tactical bankruptcy from competitive rivalry. The study also seeks to determine if there is a difference in decision-making depending on the lender's type and empirical evidence for the predictions from the theoretical model.

Material and Methods

Poverty profiling is an important statistical tool aimed at identifying the peculiarities of poverty and precisely analysing poverty situations in particular places, such as the Chakwal district in Pakistan. This dissertation especially analyses rural poverty in the Chakwal districts, using data gathered from 2018 to 2020. Punjab, the most populous province in Pakistan, with an estimated population of 127.7 million and a population density of 622 persons per square kilometre. Because to its advantageous location, the province has borders with three other Pakistani provinces: Khyber Pakhtunkhwa, Islamabad Capital Territory, Balochistan, and Azad Kashmir. In order to better manage its large population, Punjab is structured into ten administrative divisions and forty-one districts. According to the data, rural areas are home to 60% of the population, while urban areas are inhabited by 40%. An abundance of languages and cultures—including Punjabi, Saraiki, Hindko, Urdu, Pashto, Balochi, and Sindhi—make this province unique.

Punjab has achieved significant advancements in education, shown by a literacy rate that has risen to 67% during the last forty years. It has the highest Human Development Index (HDI) of all provinces in Pakistan, now at 0.564. The province government has created a network of specialized and general hospitals throughout primary, tertiary, and specialized care sectors to improve public health services. Notwithstanding Punjab's designation as an agricultural and industrial centre, several rural regions continue to face hardship, with certain populations living at or near the poverty threshold. The Pakistan Microfinance Network (PMN) plays a vital role in delivering microfinance services across the province, which is especially pertinent for our research. The study examines the allocation of microfinance loans and the quantity of borrowers.

Table 2: Distribution of sample size according to their affiliation

Respondents	Financing Source	Affiliation	Chakwal
Members	**MFI**	**Khushhali Bank**	43
		FMFB	15
		Mobilink MB	9
		NRSP MB	21
	NGO-Based MFI	**Kashf**	0
		Akhuwat (Islamic)	17

Total	**105**

Source: authors constructions

This research study focuses on analysing poverty utilizing primary data obtained via surveys, which are rated the most reliable way owing to their potential for direct connection and personal observation (Hameed et al., 2015). Albert and Collado (2004) utilized a validated questionnaire to gather data on many aspects of poverty, including demographic characteristics like gender ratios, family size, and the age of household heads. These variables were then used to examine the influence of these factors on poverty levels. The survey inquires deeply into the level of education held by respondents, the employment rate as a percentage of household size, and the availability of basic home services including running water, electricity, gas, and sewage (Datt & Jolliffe, 1999). This information is used to create an index for residential amenities and an indicator for housing assistance to measure how well these facilities are met (Sinha et al., 2017). To measure the wealth of a family, including things like farmland and cattle, an index is compiled (Ding et al., 2018). Financial factors, including land ownership and agricultural practices, are also identified as impacting poverty in the study (Lawry et al., 2014). Unfortunately, information on the precise amounts of ushar and zakat that were paid was left out since it was insufficient (Zainordin et al., 2016). Sardar et al. (2021) found that the assessment used farmland area as a correlation coefficient to look at the cultivation zones for crops including wheat, sugarcane, cotton, and rice. Studies have shown that higher levels of literacy are associated with better health and economic security for both genders, highlighting the importance of education in the fight against poverty (Hutton, 2015). An detailed examination of the determinants determining poverty in the analyzed population was provided by data for the independent variables, which were acquired from 2018 to 2020 (Abbas et al., 2020).

VIF may be classified as being under the

$$VIF = \frac{1}{1 - r^2} \qquad or \qquad VIF = \frac{1}{TOL}$$

The frequency of TOL constantly falls between 1 and 0, TOL is the inverse of VIF. TOL can be defined as:

$$TOL = \frac{1}{VIF} \qquad or \qquad TOL = 1 - r^2$$

The study highlights the importance of data preparation and analysis in comprehending individual information and mitigating data deficiencies (Singh & Masuku, 2013). It underscores the use of SPSS for the analysis of missing data and the plethora of software tools accessible for conducting supplementary tests. Data processing is necessary to enhance normalcy and transform data that fails to meet the criteria of linearity, normality, or homoscedasticity (Flatt & Jacobs, 2019). The logistic regression method is used to analyse the impact of microeconomic factors on poverty, since it provides a coherent and comprehensible framework for variable interactions (Shaffer, 2013). The model accommodates both quantitative and qualitative data, with predictor variables specified as continuous. It distinguishes between discrete random variables, which may possess values within a certain range, and binary regression models, which focus on binary outcomes (1,0) for ordinal response variables. The book examines ordinal regression techniques and suggests that the conditional or multinomial logit model is a feasible alternative for discrete research. The argument underscores the need of comprehensive data analysis in economic research.

The logistic distribution is described by Everitt (1998):

$$f(x) = \frac{\exp[x - \alpha)/\beta]}{\beta\left\{1 + \exp - [\frac{x-\alpha}{\beta}]\right\}^2} \qquad -\infty < x < \infty, \qquad \beta > 0$$

The regression analysis is a binary logistic allocation is a binary image (1,0), and this approach relies upon on the logical fraction (Maddala, 2007: Gujrati, 2005):

$$Logit\ (P_t) = \ln\frac{P_t}{1 - P_t} = \beta_0 + \sum_{j=1}^{k}\beta_i\, X_{ij} + \mu_i$$

While logit model is read as follows:
Logit(*Pi)*: Log-odd ratio interprets
Pi/1-Pi: Odd ratio in favor of being poor where:

$$P_i = \text{Prob}\ (Y_i = 1) = \frac{1}{1 + e^{-(\beta_0 + \sum_{j=1}^{k}\beta_i X_{ij} + \mu_i)}} = P_t = \text{Prob}\ (Y_i = 1) = \frac{e^{(\beta_0 + \sum_{j=1}^{k}\beta_i X_{ij} + \mu_i)}}{1 + e^{(\beta_0 + \sum_{j=1}^{k}\beta_i X_{ij} + \mu_i)}}$$

Response probability of being modeled of being poor

$$1 - P_i = \text{Prob}\ (Y_i = 0) = \frac{1}{1 + e^{(\beta_0 + \sum_{j=1}^{k}\beta_i X_{ij} + \mu_i)}}$$

Response probability to be modeled of not being poor

$$\frac{P_i}{1 - P_i} = e^{\beta_0 + \sum_{j=1}^{k}\beta_i X_{ij} + \mu_i}$$

After applying log on odd-ratio

$$\ln\frac{P_i}{1 - P_i} = \beta_0 + \sum_{j=1}^{k}\beta_i\, X_{ij} + \mu_i$$

Log-odd ratio becomes a linear function of the explanatory variables.

Logistic regression is a statistical method often used to analyse the relationship between dependent variables and predictors, particularly when the dependent variable is binary. This method uses maximum likelihood estimation (MLE) after the transformation of the response variable into logit form, facilitating a versatile relationship between the dependent variable and the predictors without requiring linearity (Wood, 2011). Maximum Likelihood Estimation (MLE) is advantageous due to its efficacy with large sample sizes and its emphasis on maximising the log-likelihood function.

The odds ratio is a fundamental concept in logistic regression since it quantifies the risk linked to certain outcomes. The odds ratio quantifies the probability of an event occurring compared to its non-occurrence (Park, 2013). In binary logistic regression, the odds ratios are represented as the exponential function of the regression coefficients (e^βj), which may be interpreted in several ways based on the predictor variables. The logit model provides parametric odds ratio estimates, but direct interpretation of coefficients does not provide significant insights into the marginal effects on the dependent variable (Breen et al., 2018). To accurately represent these marginal effects, the slope coefficients of the logit model must be modified. Traditional R^2 statistics are inadequate for evaluating the goodness of fit in logistic regression models due to the binary nature of the dependent variable, which assumes values of 0 or 1, while predicted values denote probabilities. Alternative metrics for assessing model fit are pseudo R^2, McFadden's R^2, and count R^2. R^2 values range from 0 to 1, with higher values indicating a better fit. Nevertheless, they do not surpass 1. The model's complexity increases with the number of discrete values and observations per category, complicating its implementation.

Logistic regression is particularly advantageous in evaluating poverty, since food consumption often serves as an indicator of poverty levels. The Engel Function assesses poverty by juxtaposing food expenditure with total income and classifying households according to their dietary cash flow ratio (Jayasinghe & Smith, 2021). This methodology, used by scholars like Muelbauer (1980), fails to establish minimum national standards, which is an essential element. Ercelawn's daily calorie technique investigates poverty using calorie consumption as an indication of nutritional requirements (Ercelawn, 1990). This approach presents difficulties owing to varied dietary needs determined by country, gender, age, body mass, employment, and environmental factors. Greer and Thorbecke (1986) defined food poverty as the inability to satisfy nutritional demands owing to a lack of resources, defining a poverty limit based on the maintenance of a basic nutritious diet in accordance with accepted norms.

The food insecurity technique has benefits, however it is mostly based on individual data, prioritising nutritional expenses while ignoring non-food expenditures, which may lead to data gaps (Headey & Ecker, 2013). The percentage of food to non-food expenses within total spending may be included into the food insecurity paradigm. Poverty is assessed using statistical data, with three main components: adequate well-being indicators, the construction of a dependence threshold, and the demarcation of a minimum standard to identify poverty (Coudouel et al., 2002). The emphasis is mostly on objective numerical metrics, while qualitative aspects like health and education are being acknowledged as important.

Poverty lines act as demarcations that differentiate the underprivileged from the broader populace. Multiple categories of poverty are present, including relative poverty (Laderchi et al., 2003). Poverty indicators are established by defining essential criteria and evaluating the poverty threshold (Hagenaars, 2017). The Headcount Index, a prevalent metric, identifies persons living below the poverty line but fails to provide insight into the diminishing incomes of the underprivileged, hence delivering insufficient information about their overall condition (Goedemé & Van den Bosch, 2022). The poverty gap quantifies the disparity between the income of those in poverty and the poverty threshold, signifying the resources required to bridge this deficit (Can & Can, 2023). Nonetheless, it neglects the count of those under the threshold and fails to include specific income sources, referred to be "destructive deficiencies" by Sen (1981), which might influence the comprehensive knowledge of poverty.

The Squared Poverty Gap quantifies disparity among the impoverished by assessing the severity of deprivation for each person, assigning more significance to those in extreme poverty (Mukhopadhyay, 2011). It examines distributional disparities and recognizes the intricacies of poverty. However, its application might be hard. Accurate poverty indicators are essential for understanding resource allocation and the circumstances of the disadvantaged within society (Coudouel et al., 2002). The researcher experienced various problems throughout the study, including COVID-19 limits, financial and time limitations, and everyday duties that hampered the research scope. A representative sample was chosen; nevertheless, social and cultural conventions impeded female respondents from engaging in interactive sessions (Munsch & Yorks, 2018).). Moreover, insufficient transportation and lodging in rural regions hindered data gathering. Notwithstanding these challenges, the researcher successfully collected data, underscoring the need for enhanced data gathering techniques (Leung et al., 2004).

Results and Discussion

The investigation explores socio-economic circumstances and developmental interventions in rural Punjab, comparing pre and post-scenario well-being. The Logit model evaluates variables affecting poverty reduction. The results underscore the model's efficacy in demonstrating how different factors enhance the population's overall socio-economic condition and minimize poverty levels.

Respondents Loan Cycle

The majority of the respondents fall into the cycle 4 and cycle 5 as compared to the cycle 6 or below the cycle 4 (Figure 1).

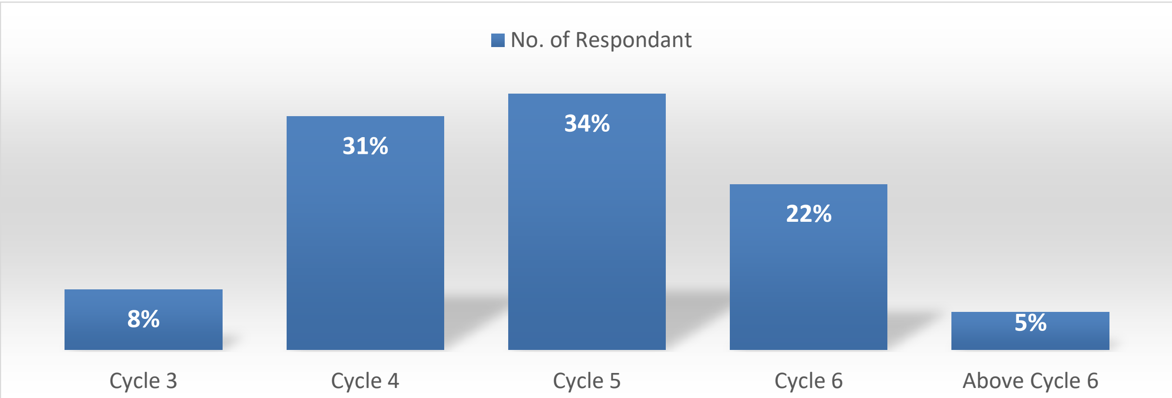

Figure 1: Respondents loan cycle period

Gender of the Respondent

The 68 percent of the respondents are fall into the male segments and 32 percent female are microfinance clients of the study (Figure 2)

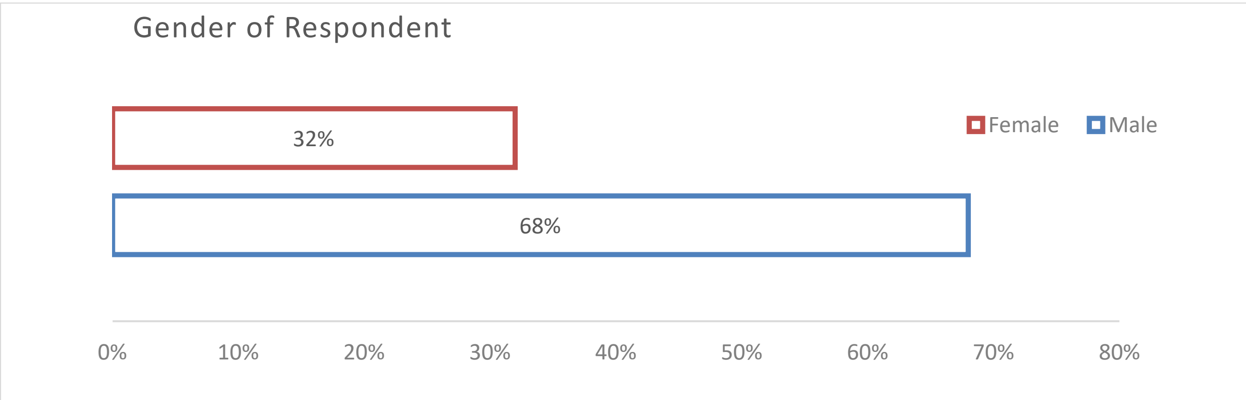

Figure 2: Gender distribution

Source: Own calculations from data of Field Survey 2018-20

Respondents' usage f Agri. Loans

The micro-credit loans are used in different segments of the agriculture fields. Majority purchased are contributed into the agriculture equipment's purchase (Figure 3).

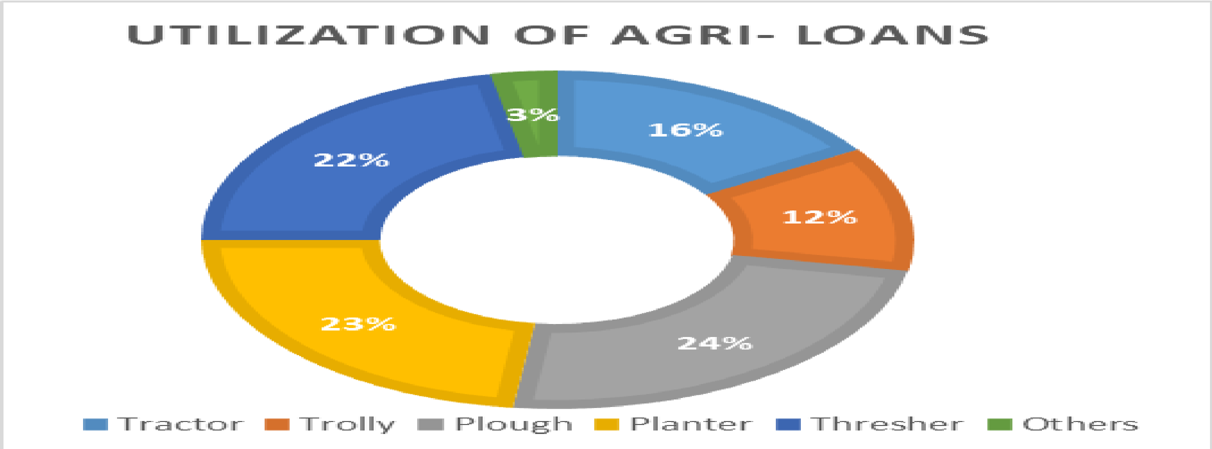

Figure 3: Agri. loans Distribution

Respondents Household Size

The household size improved with time. The household size drastically affected the increase of poverty in a negative direction (Figure 4).

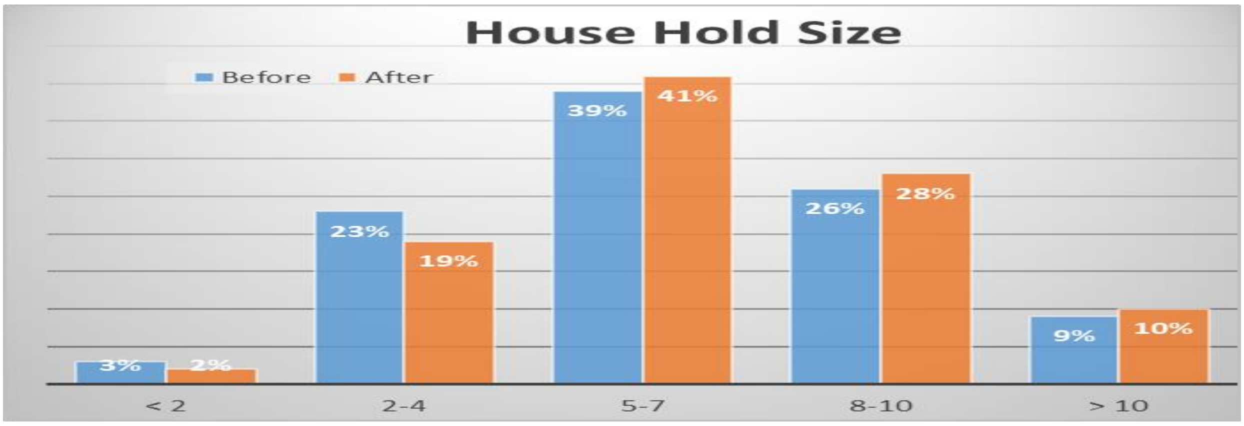

Figure 4: Household size

Borrowers' Occupation

The majority of the borrowers are engaged in the agriculture sector. So the microfinance programs should include emphasize on the agriculture sector to improve the poverty level.

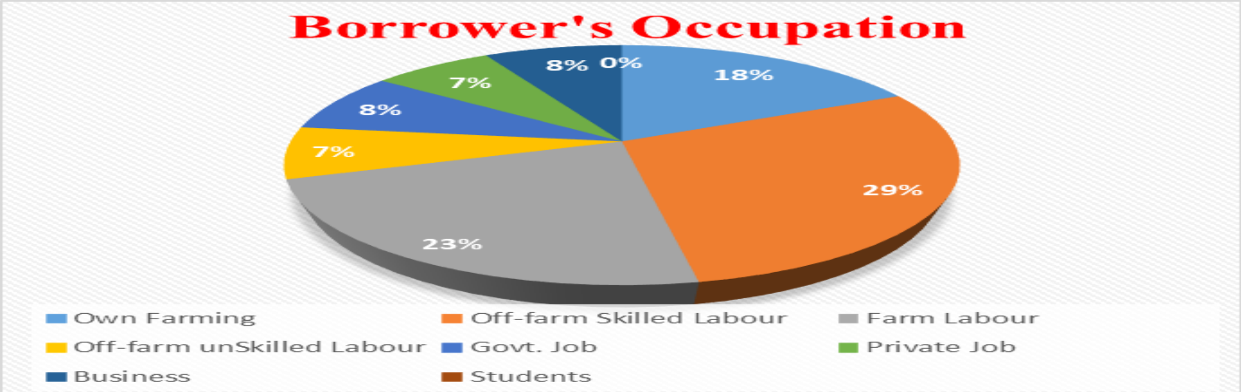

Figure 5: Borrowers' Occupation distribution

Impact of Microfinance on Absolute Poverty

Absolute poverty evaluates the amount of poverty in a population by measuring financial resources and access to vital goods and services. It sets a minimal income benchmark to differentiate between impoverished and non-impoverished persons. The poverty line in Pakistan for 2015-16 was established at PKR 3250.28 per adult per month, as per the National Poverty Report. The research examined absolute poverty using consumer price index (CPI) figures, establishing a poverty threshold of PKR 3518.87 per adult equivalent monthly for the year 2017-18. The research region's findings on several indicators of absolute poverty are encapsulated in Table 3 of the report.

Table 3: Empirical results - impact of microfinance on absolute poverty

	Households	
Absolute Poverty	**Before Credit**	**After Credit**
Absolute Poverty Headcounts		
Total Household 105	105	105
Non-Poor	68	76
Poor	37	29
Rural Poverty Headcount Ratio	35.24	27.62
Intensity of Absolute Poverty		
Poor Population (Headcount)	37	29
Intensity	13.04	8.01
Severity of Absolute Poverty		
Poor Population (Headcount)	37	29
Severity	0.29	0.09

Source: authors constructions

The poverty headcount ratio quantifies the proportion of persons living under the national poverty threshold, indicating that microfinance initiatives contribute favourably to poverty reduction. Studies demonstrate that the poverty headcount ratio decreases after the acquisition of credit, underscoring the efficacy of these initiatives in alleviating absolute poverty. The Poverty Gap Index (PGR) evaluates the severity of poverty by determining the income required to elevate persons above the poverty threshold, indicating a reduction in rural poverty intensity after credit provision. Furthermore, the squared poverty gap index assesses inequalities among the destitute, highlighting the intensity of poverty. Findings reveal that absolute poverty is less severe before loan than after, demonstrating that microfinance operations successfully ameliorate poverty in the examined region. The findings align with several national and international research, underscoring the advantageous relationship between microfinance and poverty alleviation initiatives. Overall, the data supports the assumption that microfinance plays a key role in relieving poverty and improving economic circumstances for disadvantaged communities.

Determinants of Absolute Poverty: The Logistic Regression Model

Logistic regression analysis is a prediction technique in econometrics that assesses the probability of a discrete outcome based on independent variables. It contains binary logistic regression for two categories and multinomial logistic regression for numerous categories. This research examined poverty status as a categorical dependent variable, using a binary logistic regression model with the Maximum Likelihood Estimation (MLE) method to get standard errors, coefficients, p-values, and odds ratios. Primary data was gathered from the Chakwal district in Punjab, Pakistan, before to and during credit interventions. Two logistic regression models were used to evaluate various forms of poverty, including income and multidimensional poverty attributes.

Table 4 Empirical Results - Determinants of absolute poverty (The Logit Model)

Variables	**Coefficient**	**Std. Error**	**Wald Stat**	**P-Value**	**Odd Ratio**
Farm Land Ownership	-0.104	0.079	1.455	0.178	0.788
Dependency Ratio	0.610**	0.265	4.32	0.02	1.638
Male/Female Ratio	-0.691***	0.372	3.126	0.052	0.349
Household Size	0.613*	0.122	34.45	0.000	2.012
Financial Inclusion	-0.748**	0.358	4.018	0.021	0.412
Household Head Age	-0.045*	0.02	6.425	0.004	0.731
Household Head Education	-0.115**	0.048	6.012	0.013	0.862
Post-Natal Care	-0.86**	0.473	4.321	0.034	0.781
Household Assets Index	-0.21**	0.123	3.104	0.034	0.673
Constant	-0.121	1.345	0.006	0.823	0.785

*p<.01, **p<.05, ***p<.1

Binary Logistic Regression diverges from conventional linear regression models by not conforming to assumptions such normality, linearity, and homoscedasticity. Instead, it applies a non-linear log transformation to forecast odds ratios, enabling it to handle diverse relationships.

In regression analysis, slope coefficients quantify the impact of independent factors on the dependent variable, demonstrating how variations in these variables affect response probabilities. In logistic regression, the coefficients (Bs) denote the partial effects of each predictor (Wooldridge, 2002), where positive values signify a direct association and negative values indicate an inverse relationship. The majority of independent factors correspond with anticipated results; nevertheless, the female-to-male ratio exhibits an unexpected negative coefficient, suggesting that negatively influences household absolute poverty in the studied region. This underscores the intricacy of linkages in logistic regression and the need for meticulous interpretation of results.

Interpretation of Slope Coefficients, p-Values and Odd Raito of Absolute Poverty (Binary Logistic Regression Model)

Table 4 presents an analysis utilizing binary logistic regression to investigate the determinants of absolute poverty, with absolute poverty as the dependent variable and various independent factors including farmland ownership, dependency ratio, male-to-female ratio, household size, financial inclusion, age of the household head, education of the household head, and household assets index. The results reveal a negative slope coefficient of -0.104 for farmland ownership, indicating that more ownership correlates with lower poverty levels. However, the p-value of 0.178 suggests that this link lacks statistical significance at standard confidence levels. The chances ratio of 0.788 means that a 1% increase in agricultural land ownership might lead to a 0.212% reduction in poverty, provided other variables stay constant.

Conversely, the dependence ratio exhibits a positive slope value of 0.610, showing that a larger dependency ratio corresponds with rising poverty. This link is statistically significant, with a p-value of 0.02 at the 95% confidence level. An odds ratio of 1.63 indicates that a 1% rise in the dependence ratio may lead to a 0.63% rise in poverty. The research indicates a negative slope coefficient of -0.104 for the male/female ratio, which is theoretically noteworthy, since a balanced ratio correlates with elevated income levels. A p-value of 0.052 signifies statistical significance at the 95% confidence level, while an odds ratio of 0.349 implies that a 1% rise in the male/female ratio may result in a 0.651% reduction in poverty.

The household size has a positive slope coefficient of 0.613, suggesting that bigger families often have difficulties in fulfilling their demands owing to inadequate income. This association is very significant, with a p-value of 0.0000 at the 99% level. An odds ratio of 2.012 indicates that a 1% increase in household size may lead to a 1.012% rise in poverty levels. These results were also in lined with other studies (e.g, Chowdhury, 2009; McCulloch & Baluch, 2000; Sheikh et al., 2020; Shah et al., 2021).

Financial inclusion has a negative slope coefficient of -0.748, consistent with theoretical predictions that more inclusion may alleviate poverty. The p-value of 0.021 shows statistical significance at the 95% level, with an odds ratio of 0.412 showing that a 1% increase in financial inclusion might lead to a 0.588% reduction in poverty. The age of the household head has a negative slope coefficient of -0.045, showing that older heads may possess more resources and experience, leading to lower poverty. A p-value of 0.004 signifies statistical significance at the 95% confidence level, with an odds ratio of 0.731 indicating that a 1% rise in the age of the household head may result in a 0.269% reduction in poverty. The education level of the household head has a negative slope coefficient of -0.115, suggesting that more education is associated with improved employment prospects and elevated income. The p-value of 0.013 signifies statistical significance at the 95% confidence level, accompanied with an odds ratio of 0.862 which is less then the threshold level of 1.

Conclusion

Microfinance in Pakistan is growing, but it has not successfully alleviated poverty or promoted sustainable economic growth, especially when the lower middle-class encounters escalating difficulties. The MDGs and SDGs underscore the need of poverty elimination, emphasizing the seriousness of the matter. Rural inhabitants are deprived of vital resources and financial services, resulting in social and economic marginalization. To alleviate poverty, robust economic connections among local communities, farmers, and enterprises, as well as a combination of private and state financial institutions, are necessary. Over the last four years, the microfinance industry has flourished, notably aiding individuals below the poverty line in rural Punjab who have limited access to regular banks. Nonetheless, the efficacy of microfinance in mitigating poverty remains ambiguous. This study examines the extent to which microfinance effectively mitigates inequality in rural Punjab, focusing on the influence of microfinance institutions (MFIs) and the interplay between Islamic and conventional MFIs. The research, using a structured survey of 485 families, identifies a favourable correlation between financial inclusion and poverty reduction, especially within the agricultural sector, indicating that microfinance significantly improves socio-economic circumstances in rural Punjab like district Chakwal.

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