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**ARAŞTIRMA MAKALESİ** **RESEARCH ARTICLE**

# Microcredit Participation and Farm Productivity in Pakistan: The Role of Financial Literacy, Digital Finance and Climate Shocks

Pakistan'da Mikro Kredi Katılımı ve Tarımsal Verimlilik: Finansal Okuryazarlık, Dijital Finans ve İklim Şoklarının Rolü

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## Abstract

Microcredit has long been suggested as an important tool for alleviating the financial constraints faced by small-scale farmers. However, it is also true that it cannot have an impact on farm productivity on its own. This study examines the impact of microcredit participation on farm productivity among smallholder farmers in Pakistan and investigates the moderating roles of financial literacy, digital finance use, and climate shock exposure. Primary data were collected from 384 wheat and cotton farmers in Punjab and Sindh Provinces, the obtained data were analyzed using propensity score matching (PSM) to estimate the causal effects of microcredit, and moderated regression models to identify heterogeneous effects. The findings indicate that microcredit participation is associated with significant increases in crop productivity, with wheat and cotton yields rising by approximately 13% and 16%, respectively. The productivity gains are significantly larger among farmers with higher level of financial literacy and those utilizing digital financial services. In contrast, exposure to climate shocks significantly weakens these benefits, reducing the returns to credit-financed investments and highlighting the vulnerability of agricultural production systems. Overall, the results demonstrate that the effectiveness of microcredit is highly conditional on both farmer capability and environmental risk. By integrating financial literacy, digital finance, and climate vulnerability into the analysis, this study contributes to the growing literature on agricultural finance and rural development. The findings underscore the need for integrated policy approaches that combine credit provision with financial education, digital inclusion, and climate-resilient agricultural practices to achieve sustainable productivity gains among smallholder farmers.

**Keywords:** Microcredit, Farm productivity, Financial literacy, Digital finance, Climate shocks

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## Öz

Mikrokredi, küçük ölçekli çiftçilerin karşılaştığı finansal kısıtlamaları hafifletmek için uzun zamandır önemli bir araç olarak önerilmektedir. Ancak tek başına tarımsal verimlilik üzerinde etkisinin olamayacağı da bir gerçektir. Bu çalışma, Pakistan'da mikrokrediye başvurmanın verimlilik üzerindeki etkisini, özellikle finansal okuryazarlık, dijital finans kullanımı ve iklim şoklarına maruz kalmanın bu sonuçları nasıl şekillendirdiğine odaklanmıştır. Çalışma Pencap'taki 384 küçük ölçekli çiftçiden toplanan birincil verilerden oluşmaktadır. Elde edilen veriler, mikrokredinin nedensel etkilerini tahmin etmek için eğilim puanı eşleştirme (PSM) analizi ve heterojen etkileri belirlemek için moderatörlü regresyon modelleri kullanılarak test edildi. Bulgular, mikrokredi katılımının ürün verimliliğinde önemli artışlarla ilişkili olduğunu, buğday ve pamuk verimlerinin sırasıyla yaklaşık %13 ve %16 arttığını göstermektedir. Bununla birlikte, bu kazanımlar çiftçiler arasında homojen değildir. Finansal okuryazarlık kritik bir faktör olarak ortaya çıkmakta olup, finansal olarak daha yetenekli çiftçiler krediden önemli ölçüde daha yüksek verimlilik kazanımları elde etmektedir. Benzer şekilde, dijital finansal hizmetlerin kullanımı, likidite yönetimini iyileştirerek, zamanında girdi alımlarını kolaylaştırarak ve işlem maliyetlerini azaltarak mikrokredinin etkinliğini artırmaktadır. Buna karşılık, iklim şoklarına maruz kalma bu faydaları önemli ölçüde zayıflatmakta, krediyle finanse edilen yatırımların getirisini azaltmakta ve tarımsal üretim sistemlerinin kırılganlığını vurgulamaktadır. Genel olarak, sonuçlar mikro kredinin etkinliğinin hem çiftçinin yeteneğine hem de çevresel riske büyük ölçüde bağlı olduğunu göstermektedir. Finansal okuryazarlığı, dijital finansı ve iklim kırılganlığını analize entegre ederek, bu çalışma tarımsal finansman ve kırsal kalkınma üzerine giderek artan literatüre katkıda bulunmaktadır. Bulgular, küçük ölçekli çiftçiler arasında sürdürülebilir verimlilik kazanımları elde etmek için kredi sağlamayı finansal eğitim, dijital kapsayıcılık ve iklime dayanıklı tarımsal uygulamalarla birleştiren entegre politika yaklaşımlarına duyulan ihtiyacın altını çizmektedir.


**Anahtar Kelimeler:** Mikrokredi, Tarımsal Verimlilik, İklim değişikliği, Finansal okuryazarlık, Dijital finans

## 1. Introduction

In most of the agricultural economies, access to formal financial services remain major barrier to development (Grohman et al., 2018). This is especially crucial for smallholder farmers, who depend heavily on credit to address seasonal liquidity constraints and climatic risks (Dercon and Christiaensen, 2011). Smallholder productivity is often shaped by both financial constraints and structural challenges in rural economics (Oduntan, 2025; Ginting et al., 2026). In this regard, microcredit-typically defined as small loans provided to low-income households to enable them to mobilize and utilize complementary factors of production (Islam et al., 2015; Kolapo and Didunyemi, 2024), has been widely promoted as an important development intervention. Scholars have noted that access to microcredit enhances farmers' purchasing power, enabling them to acquire essential inputs for production and that leads to positive effect on agricultural development (Kolapo and Didunyemi, 2024; Song et al., 2022). However, rural financial market is often hindered by structural constraints including information asymmetries, high transaction costs, and limited collateral availability (Addison et al., 2020) which causes financial exclusion of many smallholder farmers from formal financial system (Ullah et al., 2024), and concentration of benefits among relatively advantaged groups (Li et al., 2021; Giné, 2011). Recognizing this disparity and associated opportunities, both conventional banks and microfinance institutions have promoted access to microcredit as a mechanism for fostering adoption of modern technology (Raza et al., 2023).

Although microcredit has generated lot of optimism for poverty alleviation, it has also met by an equally vehement criticism amid to a longstanding paucity of rigorous empirical evidences (Banerjee et al., 2015a; Islam et al., 2015). For instance, several experimental studies from randomized controlled trials suggest that microcredit has heterogenous effects on business investment, consumption, and poverty reduction (Banerjee et al., 2015b; Karlan and Zinman, 2011) thereby challenging the narrative of transformative change. Furthermore, few studies have also discussed that microcredit access doesn't have significant effect on profitability, it only helps in risk coping and modifies financial behavior (Islam et al., 2015; Karlan and Zinman, 2011). Such conflicting findings have led to a scholarly debate on whether effectiveness of microcredit hinges on borrower characteristics, contextual factors, or complementary conditions (Beck et al., 2009; Field et al., 2013; Islam et al., 2015).

Furthermore, researchers have often stressed that though credit access is necessary, it may not guarantee its productive use (Karlan and Morduch, 2010). Together with supply side infrastructure that delivers financial services, borrower capability is also extremely important for productive use of microcredit (Grohmann et al., 2018). Because, borrowers are different from each other based on their capacity to use loans productively, and such differences stems from disparities in financial capability, access to enabling technologies, and vulnerability to environmental and economic risks. This emerging viewpoint suggest that microcredit's effects are highly heterogenous, varying across institutional, socioeconomic, and environmental contexts. While previous studies have examined the average effects of microcredit on agricultural outcomes, little attention has been paid to understanding the conditions under which credit generates productivity gains. Existing literature has highlighted three interrelated factors in explaining microcredit outcome in rural economies: Financial literacy, digital financial inclusion, and climate shocks. Literature indicates that microcredit borrowers are often vulnerable to debt stress, over-indebtedness, and repayment challenges (Kar, 2018). In response to these challenges, researchers and practitioners have advocated financial literacy initiatives as a mean of strengthening borrower's financial management capacity (Bylander et al., 2019). Financial literacy improves farmer's ability to manage debt obligations, investment allocation, and overall financial decision making (Lusardi and Mitchell, 2014). Conversely, without sufficient financial knowledge access to credit may prove detrimental to borrowers' economic well-being (Giné and Klonner, 2005). While financial literacy enhances borrowers' capacity to utilize credit effectively, the institutional and technological environment within which credit is delivered shapes its ultimate impact. Rural financial architecture has gone significant transformation in developing economies such as Pakistan due to explosion of digital technologies (Shah and Zaidi, 2023). However, the adoption of digital platforms hinges on user confidence in their integrity and safety, especially in contexts characterized by increasing cyber-related fraud (Idrees et al., 2025). A World Bank report reveals that, introduction of digital technology has opened up new opportunities for rural areas through financial services (World Bank, 2012). Digital financial services can amplify the benefits of microcredit by reducing transaction costs, improving liquidity management, and facilitating timely loan disbursement (Beck et al., 2018). Improved financial access, in turn, accelerates the adoption and diffusion of productivity-enhancing agricultural technologies (Kou et al., 2020).

A third critical factor shaping microcredit outcomes concerns farmers' exposure to climate-related shocks. Smallholder farmers in developing economies are typically ill-equipped to cope with climate variability (Dercon and Christiaensen, 2011). Climate shocks constitute a major constraint on farm productivity, often undermining accumulation of productive capital that credit interventions attempt to foster (Bakare et al., 2023). Thus, climate shocks transform perceived repayment risk into actual default risk. Empirical evidence indicates that higher perceived repayment risk significantly discourages both credit demand and supply (Ullah et al., 2024). By generating actual income and asset losses, climate shocks undermine the feasibility of investments funded through credit. Large-scale climatic events, including droughts and floods are sever, and often result in significant yield declines and income contractions that exceeds beyond the immediate shock period (Dercon and Christiaensen, 2011; Delaporte and Maurel, 2018; Younas et al., 2024). The impact of climate shocks depends critically on farmers' ability to insure against risk, which in turn is shaped by access to financial markets (Islam and Maitra, 2012). Evidences show that impacts of climate shock are not uniform, the poorest household struggle most, and forced into costly coping strategies that compromise long-term recovery (Carter et al. 2007). To reduce the risk of shocks farmers will consciously take some adaptive measure (Xu et al. 2017). For example, Belton et al. (2021) suggested that farmer will reduce the impact of climate change on agricultural production by increasing the level of mechanization, improving irrigation facilities and changing crop varieties. As investment in agriculture help farmers to be more flexible in responding to risk posed by changing climate, therefore, climate shocks can increase the demand for credit beside its negative effects on productivity.

Despite the growing recognition of these factors, few empirical studies have thoroughly investigated how financial literacy, digital finance and climate shocks collectively affect the influence of microcredit on farm productivity. This study therefore aims to addresses this gap by utilizing the primary data collected from small farmers in Punjab, Pakistan. This study makes three important contributions. First, it uses the propensity score matching (PSM) to estimates the unbiased average treatment effect of microcredit participation on farm productivity. Second, it explicitly examines the moderating effects of financial literacy, the use of digital finance, and climate shock exposure, using interaction models. Third, it provides evidences pertinent to policy regarding how complementary interventions can enhance developmental impact of microcredit in vulnerable farming communities.

## 2. Literature Review

### *2.1. Microcredit and Farm Productivity*

From an agricultural finance perspective, credit serves as a productive input that enables farmers to overcome seasonal liquidity constraints, smooth cash flows, and invest in yield-enhancing technologies (Ullah et al., 2024). Therefore, the relationship between agricultural credit and farm productivity has become a central theme within agricultural economics. Theoretical foundation of microcredit is grounded in theory of credit market imperfection, which states that information disparities and collateral constraints limit low-income households' ability to invest in productive assets (Stiglitz and Weiss, 1981). According to Feder et al. (1990) in absence of perfect capital market, credit bridges the gap between input requirements and available cash flow, thereby facilitating timely investment in seed, fertilizers, and machinery. Microfinance institutions support the adoption of yield enhancing technologies when there is limited internal capital accumulation. Furthermore, sustainable livelihood framework stresses that credit enables the acquisition of complementary assets that help in improved agricultural outcomes. Despite a strong theoretical foundation, the universalist claims about microcredit impacts have been challenged in the emerging literature, implying that microcredit outcomes vary substantially across context due to difference in institutional quality, borrower characteristics, and environmental risk (Banerjee et al., 2015a).

Studies carried out in developing countries (South Asia and Sub-Saharan Africa) provides mixed evidence regarding the potential of microcredit to improve farm productivity. For example, evidences from Nigeria shows a strong positive impact of microcredit on farm productivity. Bakare et al. (2023) found that access to microcredit leads to significant increase in rice yields, with an average treatment effect on the treated (ATT) of 0.930, indicating that credit users substantially outperform non-users. Some other, quasi-experimental studies have also shown that, yields, household incomes, and asset accumulation have all significantly improved following the participation in microcredit programs (Islam et al., 2015; Imai et al., 2010; Jimi et al., 2020). While some other studies suggest that impact of microcredit is not automatic (Grohmann et al. 2018). Rayhan et al. (2023) found in their study on

rice farming in Bangladesh that, capital availability is crucial but not sufficient, the adoption of farm technology which leads to boost productivity depends on how credit constraints are alleviated. This is also in line with the broader critique from RCTs, which argue that credit alone may not yield significant improvements in the productivity without complementary conditions (Banerjee et al., 2015a; Karlan and Zinman, 2011).

Empirical evidences from Pakistan suggest a generally positive influence of microcredit on farm. For example, Khan et al. (2020) reported that participation in microfinance programs significantly enhanced farm productivity among farming households in Khyber Pakhtunkhwa province, suggesting that improved access to finance facilitates investment in productivity-enhancing inputs and technologies. However, distribution of benefits may be uneven, recent research suggest a greater effect on medium-sized farmers than on marginal one (Ullah et a., 2024), indicating a heterogeneity in impacts that this study aims to investigate.

Following the theory of credit market imperfection (Stiglitz and Weiss, 1981) that suggests that "liquidity constraints prevent optimal investment in productive assets and empirical evidence it is hypothesized that;

H1: Participation in Microcredit program has a positive effect on smallholder farmers' farm productivity.

### *2.2. Financial Literacy*

Financial literacy which has been defined as, "individuals' ability to understand and apply financial principles, has been regarded as a crucial concept in the context of agricultural finance (Lusardi and Mitchell, 2014). Due to digitization of financial services, digital financial literacy has become a crucial requirement for mitigating risks associated with technology-mediated transactions (Idrees et al., 2025). Digital financial literacy encompasses competencies such a platform navigation, digital account management, and risk evaluation. In this regard, literature shows that individuals with higher level of financial knowledge are more likely to indulge in investment activities, bear financial shocks, and diversify their asset portfolios (Bialowolski et al., 2022). Maji and Laha (2023) argued that financial literacy contributes significantly to individual financial stability and long-term economic security in developing and agrarian economies.

Emerging empirical evidences suggest that higher level of financial literacy is associated with better investment efficiency and lower credit default risk (Grohman et al., 2018; Hussain et al., 2023). For example, Das and Maji (2023) found a positive relationship of financial literacy with responsible saving and borrowing behavior, suggesting its broader relevance to agricultural finance. Similarly, Raza et al. (2023) reported that financially literate farmers in Pakistan are more likely to avail microcredit and invest in quality inputs, which in return causes higher crop yields. Additionally, Rahim et al. (2024) suggested that financially literate farmers are less vulnerable to over-borrowing and more likely to invest in yield enhancing technologies. Expanding consequence of limited financial knowledge, Giné and Klonner (2005) warned that farmers with low financial knowledge may misuse loans, fall into debt trap, or underinvest in productive technologies. Karlan et al. (2014) argued that financial knowledge determines whether microcredit will finance productive asses or consumption expenditures. Collectively, these studies have emphasized that financial literacy strengthens long-term financial planning and decision-making quality by enhancing farmers' ability to evaluate investment returns, assess market risks, and adapt to price fluctuations (Abubakar et al., 2019; Lusardi et al., 2020. It is therefore hypothesized that financial literacy positively moderates the relationship between microcredit participation and farm productivity

H2: Financial literacy positively moderates the relationship between microcredit participation and farm productivity.

### *2.3. Digital Finance*

According to Song et al. (2022) "digital finance refers to the integration of internet technology with traditional financial services, creating new models for financing, payment, and investment." In the context of agriculture, researchers have identified several channels through which digital finance operates. Beck et al., (2018) argued that digital financial tools such as mobile wallets, mobile banks, peer-to-peer lending, and blockchain-based credit have reduced transaction costs, enhanced loan disbursement efficiency, and increased financial inclusion. By reducing the transaction cost and delays in loan disbursement, digital finance can improve the outcomes of financial inclusion. In Pakistan, Easypaisa, Upaisa, and Jazzcash are the examples of mobile money services that have reduced liquidity constraints (Shah and Zaidi, 2023).

Moreover, Digital financial inclusion has been recognized as critically important to enhance agricultural capacity of the farmers through access to modern technology and timely inputs. For example, Zhai et al. (2023) by using a dynamic panel data (2011-2018) from rural China showed that digital financial inclusion promotes technological adoption and efficiency gains, resulting into enhanced farm productivity. Empirical evidences from Uganda also indicate that digital innovation in microcredit delivery lowers barriers to input acquisition and improve output and profitability (Mukaila, 2024). Similarly, Jack and Suri (2014) reported that digitalization of microfinance operations in India and Bangladesh has improved service efficiency, repayment rates, household resilience, and consumption smoothing. Collectively, these studies indicate that digital finance enhances microcredit effectiveness by accelerating transactions, reducing transaction costs, and expanded access to complementary financial services. It is therefore hypothesized that the productivity impact of microcredit will be stronger among farmers who use digital financial services.

H3: Digital finance positively moderates the relationship between microcredit participation and farm productivity.

### *2.4. Climate Shocks*

Climate change has become one of major threats to smallholder agricultural systems globally and it is widely perceived by the farmers. In a study by Bakare et al. (2023) it was observed that, 98.7% rice farmers reported impacts of climate change on their farms, with 43% directly experiencing yield reductions. According to the Sustainable Livelihoods Framework, climate change adversely impacts asset bases (natural, physical, and financial), diminish the ability of farmers to invest and benefit from microcredit. Recurring floods and extreme weather events have frequently disrupted crop yields, making rural communities more vulnerable (Younas et al., 2024). Moreover, exposure to covariate climate shocks may create disincentive for productive investment, implying credit may not be used for its intended purposes. This dynamic is consistent with the theory of risk induced poverty trap (Dercon and Christiaensensen, 2011) which implies that farmer may be stuck with low return, low risk activities without means to ensure consumption, even when credit is available, trapping them in poverty and limiting the productive use of microcredit.

While climate shocks pose significant risks, microcredit may also serve as a mechanism for strengthening farmers' resilience. Evidence indicates that access to credit enhances farmers' capacity to adopt climate-adaptive technologies, highlighting a dynamic interaction between financial access and climate risk (Bakare et al. 2023). At the same time, adverse climatic conditions can reduce expected returns on credit-financed investment by eroding yields, damaging capital assets, and increasing debt burdens (Hill and Viceisza, 2012). Broader projections estimates suggest that climate-related disruptions may reduce farm productivity in developing countries by 5–10% (Baptista et al., 2023). Similarly, evidence from Ghana further indicates that droughts and excessive rainfall undermine farmers' input adoption, thereby constraining the effectiveness of agricultural development interventions.

Despite growing interest in both climate risk and microfinance, the interaction between climate shocks and microcredit remains insufficiently examined in the existing literature. Emerging evidence suggests that the long-term resilience of microcredit can be strengthened by integrating credit access with climate risk mitigation instruments such as crop insurance, drought-resistant seeds, and flexible repayment arrangements (Carter et al., 2007; Carter et al., 2018). More broadly, recent impact evaluation research emphasizes the importance of examining heterogeneous treatment effects rather than relying solely on average treatment estimates (Angelucci et al., 2015; Bauchet et al., 2011). The effectiveness of microcredit is increasingly understood as contingent upon contextual and individual-level characteristics (Beck et al., 2009; Karlan et al., 2014). These findings lead to the following hypothesis

H4: Climate shocks negatively moderate the relationship between microcredit participation and farm productivity.

## 3. Data and Methodology

### *3.1 Research Design*

This study adopts a quantitative cross-sectional design to estimate the association between microcredit participation and smallholder farm productivity in Pakistan, while examining the moderating roles of financial literacy, digital finance use, and climate shock exposure. To mitigate selection bias and examine effect heterogeneity, the study integrates propensity score matching with interaction-based regression models. PSM is employed because microcredit participation is non-random, selection bias may arise if observable characteristics differ between treated and untreated farmers. By matching farmers on relevant covariates such as age, education, and farm size, PSM approximates a counterfactual group comparable to treated farmers in observed characteristics (Chen et al., 2025). Post-matching regression analysis with interaction specifications is employed to test moderation effects. This combined approach is increasingly applied in agricultural development research to identify conditional treatment effects in contexts where program impacts depend on environmental and institutional factors (Bakare et al., 2023; Kipkogei et al., 2025).

### *3.2 Sampling and Data Collection*

Punjab and Sindh provinces were chosen as a universe of the study, the selection of these two provinces is based on their cumulative share of above 80% in agriculture output of the country and concentration of majority of microcredit beneficiaries in these regions. Additionally, these two provinces were deemed to be appropriate for evaluation of microcredit impacts due to substantial heterogeneity in farm size and climate exposure. The sampling frame of the study comprises of smallholder wheat and cotton farmers with potential access to microcredit sources.

To ensure statistical representativeness, the minimum sample size was calculated using Cochran's (1977) formula for proportions:

$$\eta_0 = \frac{\mathrm{Z}^2\, p(1-p)}{e^2} \qquad \text{(Eq. 1)}$$

Where, $Z$ = 1.96 (95% confidence level), $p$ = 0.5 (maximum variability), and $e$ = 0.05 (margin of error). This yielded a minimum required sample of 384 respondents.

Sample of the study was selected using a multistage stratified random sampling technique. Two districts were purposively selected from each province at the first stage; Multan and Faisalabad from Punjab Province and Sukkur and Hyderabad from Sindh. In the second stage, tehsils within each selected district were randomly chosen, followed by the random selection of villages. At the final stage, systematic random sampling was used to select individual households from official agricultural extension records. In this way, a sample of 384 smallholder farmers was generated. A structured questionnaire was used to collect primary data from the smallholders through a face-to-face interview. The questionnaire comprised various sections, socio-demographics and farm characteristics, credit participation and use, farm productivity, financial literacy, digital finance adoption, climate-shock exposure, and institutional trust. A pilot survey was conducted before full-scale fieldwork to refine question wording and ensure measurement consistency. To further ensure consistency in data collection, enumerators were trained prior to the fieldwork, and data was collected between July-October 2024. To minimize recall bias, agricultural yields were recorded for the most recent production cycle (2023–24 season), and financial variables were cross-validated where possible through loan records or transaction receipts.

### *3.3 Variables and Measurements*

The study included both dependent and independent variables, along with moderating and control variables, all measured using validated indicators from recent literature to ensure scientific rigor and comparability.

*Farm Productivity* which is a dependent variable in this study was measured as crop yield per acre for the two major crops in the sample regions (wheat and cotton). Farmers reported their total harvested quantity in mounds (1 mound ≈ 40 kg), which was then divided by cultivated area. Yield data were cross-verified with local agricultural extension officers to minimize recall bias. Following Bakare et al. (2023) and Kipkogei et al. (2025), productivity was treated as a continuous variable (mounds/acre) and analyzed separately for each crop. Microcredit Participation which is a key independent variable was coded as a binary variable; 1 = farmer accessed microcredit from a formal or semi-formal source in the last two years (microfinance bank, agricultural cooperative, or NGO),

0 = no access to microcredit in the same period. Microcredit participation was initially identified through self-reports, where possible, verified with institutional records to enhance data reliability, in line with established survey validation practices (Sahu et al., 2024; Phan et al., 2023).

Financial Literacy which is a moderating variable in thus study was adapted from Raza et al. (2023) and Rahim et al. (2024). The index captures competencies such as numerical reasoning, budgeting, understanding of loan contract, and risk awareness. Each component was assessed using three structured multiple-choice items. Binary scoring was applied to each item, where correct responses was coded as 1, and incorrect responses as 0. Financial Literacy Index was computed as:

$$FLI = \frac{\Sigma_i^k X_i}{k} \quad \text{(Eq. 2)}$$

Where $X_i$ = score for item *i*, k = total number of items (12). The index ranges from 0 to 1, where values closer to 1 indicate stronger financial knowledge and decision-making capacity. Equal weights were assigned to all financial literacy items because each question captures a fundamental dimension of financial capability. Alternative approaches, such as principal components analysis, were also considered, however, the equal-weighting method was preferred due to its simplicity and ease of interpretation.

*Digital finance* use is another moderating variable, and it was measured as a binary variable, coded as 1 for farmers engaging in mobile-based financial transactions related to agriculture within the previous year, and 0 otherwise, consistent with Kim and Duvendack (2025) and Mukaila (2024). To enhance reliability, respondents were further asked to report the number of digital transactions conducted in the preceding six months.

*Climate shocks* exposure was measured using a cumulative shock incidence index adapted from Yu et al. (2025) and Lane (2024). Farmers reported whether they had exposure to four major climate events floods, droughts, extreme rainfall, or heatwaves during the past year. Affirmative responses were coded as 1 and negative responses as 0. The cumulative Climate Shock Exposure (CSE) score ranged from 0 to 4, with scores closer to 4 indicating higher levels of climatic vulnerability.

The model controls for key demographic and socioeconomic characteristics consistent with existing empirical literature (Kandie and Islam, 2022; Ogunleye et al., 2024), including age, education, farm size, institutional trust (Likert scale 1–5, adapted from Nuruzzaman et al., 2025), and off-farm income. Both institutional trust and financial literacy were operationalized as composite latent variables derived from multiple indicators. Internal reliability was evaluated using Cronbach's alpha coefficients, and all constructs exceeded the recommended 0.70 reliability threshold (Nunnally, 1978) and all constructs exceeded the recommended 0.70 reliability threshold.

### *3.4 Empirical Strategy*

The key empirical challenge in estimating the causal effect of microcredit participation is potential self-selection bias farmers who choose to participate may differ systematically from non-participants in both observable and unobservable ways. To overcome this, we followed the approach of Islam et al. (2015), and employed PSM to address the self-selection bias arising from observable differences between participants and non-participants.

#### *3.4.1. Propensity Score Matching*

At the first stage, PSM was employed to estimate the average treatment effect on the treated (ATT) by constructing a counterfactual group of non-participants with similar observable characteristics. The propensity scores were estimated using a Probit model:

$$P(T_i = 1|X_i) = \phi(X_i\beta) \quad \text{(Eq. 3)}$$

Where $T_i$ indicates microcredit participation, $X_i$ is the vector of covariates, and Φ is the standard normal distribution. The covariates include all control variables mentioned above, following the balancing property requirement. Kernel matching (with bandwidth = 0.06) was used as the primary matching algorithm to minimize variance while maintaining bias reduction (Rosenbaum and Rubin, 1983). Common support was enforced to ensure overlap between treated and control units. Balance diagnostics were conducted by comparing standardized mean differences before and after matching. Post-matching SMDs below 5% were considered evidence of good balance (Caliendo and Kopeinig, 2008).

### *3.4.2. Moderated Regression Models*

While PSM addresses observable selection bias, it does not allow for heterogeneity analysis. Therefore, at the second stage, moderation models on the matched sample were measured to examine whether the effects of microcredit vary across financial literacy, digital finance, and climate shock exposure. The model takes the following form:

$$Yi=\alpha + \beta1Microcredit_i + \beta2Moderator_i + \beta3(Microcredit_i \times Moderator_i) + \gamma Xi + \epsilon i \quad \text{(Eq. 4)}$$

Where, Yi = agricultural yields, $Microcredit_i$ is a participation indicator, $Moderator_i$ = financial literacy, digital finance, climate shock exposure, institutional trust, γXi= vector of control variables. A positive and significant value of β3 suggest that the moderator strengthens the productivity effects of microcredit; a negative value of β3 suggests weakening.

### *3.4.3. Robustness and Sensitivity Checks*

To verify the stability of the results of the study, various robustness checks were conducted, such as nearest neighbor matching with caliper 0.1, Placebo tests to estimate ATT on outcomes unrelated to credit (e.g., non-agricultural expenditures) to test for spurious matches, Rosenbaum (2002), bounds sensitivity analysis to test how strong unobserved confounding would need to be to invalidate results and exclusion of extreme outliers from yield distributions. All robustness checks confirmed the reliability of the primary results.

## 4. Results

### *4.1 Descriptive Statistics and Balance Tests*

Table 1 presents the descriptive statistics for key variables before and after propensity score matching (PSM). The pre-matching sample shows significant mean differences between microcredit users and non-users in education, financial literacy, institutional trust, and off-farm income. After matching, all standardized mean differences are within the recommended 10% threshold, it is confirmed that the PSM successfully balanced observable characteristics between borrowers and non-borrowers, supporting the validity of subsequent treatment effect estimates.

***Table 1. Descriptive Statistics and Covariate Balance Before and After Matching***

| Variable | Mean (Treated) | Mean (Control) | Std. Mean Diff. (Before) | Std. Mean Diff. (After) |
|---|---|---|---|---|
| **Age (years)** | 41.6 | 42.2 | 0.08 | 0.02 |
| **Education (years)** | 9.3 | 7.6 | 0.25 | 0.04 |
| **Landholding size (acres)** | 7.8 | 7.1 | 0.17 | 0.05 |
| **Financial literacy index** | 0.64 | 0.48 | 0.32 | 0.06 |
| **Institutional trust** | 3.82 | 3.27 | 0.29 | 0.05 |
| **Digital finance use** | 0.54 | 0.37 | 0.31 | 0.07 |
| **Off-farm income (PKR/year)** | 153,400 | 122,200 | 0.22 | 0.06 |
| **Climate shock exposure** | 1.13 | 1.08 | 0.07 | 0.03 |

Note: All continuous variables are standardized before matching. Balance tests based on Nearest Neighbor Matching (1:1, caliper = 0.05)

### *4.2 Determinants of Microcredit Participation*

The determinants of microcredit participation were estimated using a probit model and results are presented in Table 2. Education and financial literacy have significant positive influence on the probability of participation in a microcredit program, results are consistent with Raza et al. (2023) and Namayengo et al. (2025), they found that cognitively capable farmers are more confident in engaging with formal credit systems. Similarly, institutional trust and digital finance adoption appear to lower transaction barriers and enhance probability of borrowing (Mukail, 2024; Yu et al., 2025).

*Table 2. Determinants of Microcredit Participation*

| Variable | Coefficient | z-statistic | p-value |
|---|---|---|---|
| **Age** | -0.011 | -0.93 | 0.351 |
| **Education (years)** | 0.081 | 2.15 | 0.032 |
| **Landholding Size (acres)** | 0.057 | 1.45 | 0.147 |
| **Financial Literacy Index** | 0.234 | 3.45 | 0.001 |
| **Institutional Trust** | 0.198 | 3.02 | 0.002 |
| **Digital Finance Use** | 0.429 | 2.78 | 0.006 |
| **Climate Shock Exposure** | 0.113 | 0.94 | 0.348 |
| **Off-Farm Income** | 0.0007 | 2.11 | 0.035 |
| **Pseudo $R^2$ = 0.316** | **Likelihood ratio $\chi^2$ = 87.23 (p < 0.001)** | | |

### *4.3 Impact of Microcredit on Farm Productivity (PSM Estimates)*

The PSM results given in Table 3 show that microcredit has a statistically significant and positive impact on farm productivity. These findings have multiple implications; first they confirm the earlier findings that Access to microcredit facilitates purchase of productivity enhancing inputs (Islam et al., 2015; Khan et al., 2020). Secondly, the findings also mirror recent empirical studies (Bakare et al., 2023) those indicate that impacts of microcredit are more restrained that early microfinance narratives.

*Table 3. ATT Estimates (Post-Matching)*

| Crop | Matching Algorithm | ATT (mounds/acre) | Std. Error | t-statistic | p-value |
|---|---|---|---|---|---|
| **Wheat** | Nearest Neighbor | 4.31 | 1.02 | 4.22 | 0.000 |
| **Wheat** | Radius (0.05) | 4.28 | 1.14 | 3.76 | 0.000 |
| **Wheat** | Kernel | 4.25 | 1.21 | 3.51 | 0.001 |
| **Cotton** | Nearest Neighbor | 3.12 | 1.06 | 2.94 | 0.004 |
| **Cotton** | Radius (0.05) | 3.08 | 1.11 | 2.77 | 0.006 |
| **Cotton** | Kernel | 3.01 | 1.23 | 2.45 | 0.014 |

### *4.4 Moderation Model*

Moderation results presented in Table 4 indicate that impacts of microcredit are context-dependent rather than uniform. The statistically significant and positive interaction between microcredit and financial literacy ($\beta = 0.148$, $p < 0.05$) shows that farmers with higher level of financial literacy gains higher productivity returns of microcredit. Similarly, significant and positive interaction effect of institutional trust on productivity returns of microcredit in Model 2 ($\beta = 0.132$, $p < 0.05$) suggest that confidence in financial institutions promotes more efficient investment decisions. the model 3 reveals that digital finance has strongest interaction effect ($\beta = 0.172$, $p < 0.01$), implying that digital finance significantly strengthens credit effectiveness. While, significant and negative interaction between microcredit and climate shock exposure (($\beta = -0.162$, $p < 0.05$) in Model 4, suggest that climate shocks erode the returns to credit financed agricultural activities. Summing up, moderation model results strengthen the argument that microcredit effectiveness is contingent upon, institutional, knowledge, technological, and environmental factors.

*Table 4. Results of Moderation Models*

| Variable | Model 1 (FLI) | Model 2 (IT) | Model 3 (DFU) | Model 4 (CSE) |
|---|---|---|---|---|
| **Microcredit (MC)** | 0.267*** | 0.259*** | 0.254*** | 0.241*** |
| **Moderator** | 0.193** | 0.176** | 0.215*** | -0.174** |
| **MC × Moderator** | 0.148** | 0.132** | 0.172*** | -0.162** |
| **Controls (age, education, landholding, off-farm income)** | Included | Included | Included | Included |
| **$R^2$** | 0.314 | 0.308 | 0.327 | 0.302 |
| **F-statistic** | 15.72*** | 15.11*** | 16.81*** | 14.29*** |

***p < 0.05; **p < 0.01; ***p < 0.001**

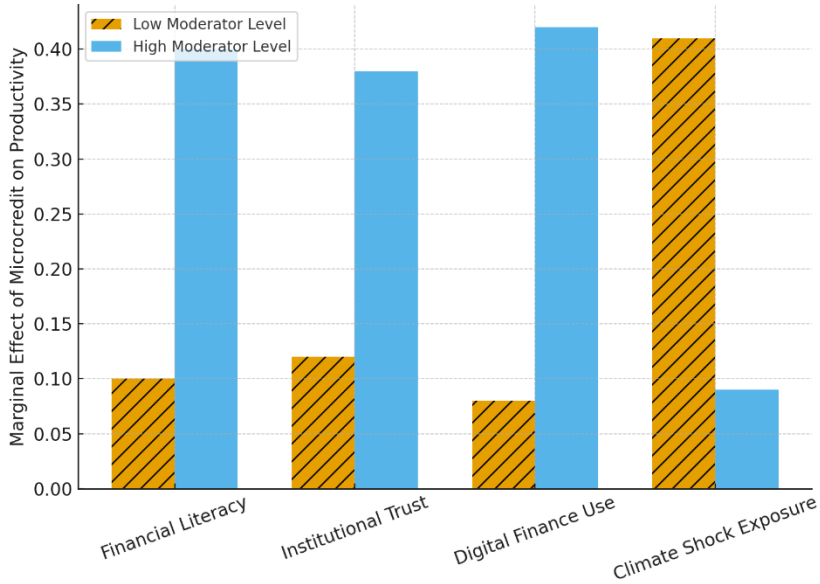



***Figure 2. Interaction Effects of Moderators on the Microcredit–Productivity Relationship***

Marginal effects of microcredit are shown in the Figure 2, which reveals that financial literacy, institutional trust, and digital finance use amplifies that microcredit impacts on productivity.

## 5. Discussion

### *5.1. Determinants of Microcredit Participation*

The present study analyzed three interconnected dimensions. First, using a probit regression model it identified the determinants of farmers' participation in microcredit programs. Second, the average productivity effects of participation in credit were evaluated using propensity score matching. Thirdly, the conditional impact of credit under varying levels of financial literacy, digital finance use, and climate exposure was analyzed using moderation analysis. The results of the study contribute to the ongoing debate around effectiveness of microfinance by underscoring the dependent of credit effectiveness on institutional quality, borrowers' characteristics, and contextual risk exposure.

Results of probit regression model reveal that education, off-farm income, financial literacy, institutional trust, and digital finance significantly increase the probability of credit participation. These results suggest that informed borrowers face lower informational barriers and great confidence in engaging with formal lenders consistent with the prior research that shows that financing knowledge as a facilitator to financial inclusion (Cole et al., 2011; Lusardi and Mitchell, 2014). Furthermore, digital finance use highlights in expanding financial inclusion. While institutional trust suggests that confidence in financial institutions and regulatory frameworks reduces perceived risk and increases participation rate (Guiso et al., 2004). Similarly, farmers characteristics such as education and off-farm income increase likelihood of participation, former by enhancing procedural understanding, while later may strengthen perceived credit worthiness. However, age, landholding size, and climate shock exposure do not significantly predict participation in credit programs. These results suggest that access is driven more by capability and institutional factors than farm scale or age.

### *5.2 Average Productivity Effects of Microcredit*

Results of average treatment effects shows an increase of approximate 13-16% in the yield, and results are aligned with findings of the previous studies conducted in similar agro-ecological settings. Similar results are reported by Bakare et al. (2023), they also showed that microcredit participation significantly increased rice yields in Nigeria. The results are further supported by previous microfinance research in South Asia and Sub-Saharan Africa demonstrating that credit access enhances smallholder productivity (Islam et al., 2015; Imai et al., 2010; Jimi et al., 2020). The observed effects likely reflect that credit facilitates investment in improved inputs, technological adoption, and more stable production practices. However, estimated effect size is small compared to earlier studies that projected larger welfare impacts of microcredit (Khandker and Samad, 2014). These results are

consistent with emerging evidences that suggest that microcredit when implemented as a standalone intervention yield limited results (Karlan and Zinman, 2011; Banerjee et al., 2015b). Though estimated productivity gains are economically significant, however, the magnitude of benefits depends on farmers' financial capability, access to supportive technologies, and exposure to climate risks. These findings motivated the subsequent analysis of moderating factors those influence the effectiveness of microcredit interventions.

### *5.3. Financial Literacy*

The results of moderation model reveal an amplifying role of financial literacy in productivity impact of microcredit, suggesting that farmer with higher financial literacy realize greater productivity impact of microcredit. This fining is aligned with previous studies that found that financially literate farmers are better equipped to asses investment profitability, evaluate returns, avoid over-debtness and optimize input allocations (Cole et al., 2011; Field et al., 2013; Lusardi and Mitchell, 2014). Furthermore, results resonate with the findings of the studies from both developing and developed economies showing that financial literacy and credit access operate symbiotically, and in the absence of adequate financial knowledge credit program may yield limited benefits or unintended consequences (Giné and Klonner, 2005; Hussain et al., 2023).

### *5.4. Digital Finance*

The results show that digital finance positively moderates the relationship between credit access and productivity outcomes of microcredit, suggesting that technology enhances the efficiency of credit utilization. Though literature shows limited direct effects of digital finance on farm productivity (Liu et al., 2021) The results reveal that farmers using digital financial platforms are more likely to have higher productivity benefits compared to no-users. The results are aligned with Idrees et al. (2025), they also reported conditional role of digital finance in enhancing credit effectiveness. This positive effect possibly operates through improved liquidity management, faster loan disbursement, better financial record keeping, and reduced transaction costs as reported in relevant literature (Beck et al., 2018; Yu et al., 2022). Similarly, Zhai et al. (2023) stressed that digital financial inclusion lessens rural financial constraints by reducing transaction costs and improving managerial capacity. Furthermore, previous studies (Jack and Suri, 2014; Munyegera and Matsumoto, 2018) have also shown that digital platforms provide farmers with access to market prices, financial education, real time information, and weather forecasts that may have favourable effect on production planning and resource allocation leading o improved productivity.

### *5.5. Climate Shocks*

Contrary to the strengthening role of financial literacy and digital finance, climate shock exposure constrains the productivity improvement associated with microcredit. The results indicate central role of risk in shaping credit outcomes, reinforcing the findings of the previous research that shows that perceived repayment risk significantly reduces microcredit utilization (Ullah et al., 2024). Climate shocks though asset or income losses transform perceived risk into tangible financial strains. The findings support the theoretical relationship between perceived risk and realized shocks confirming that credit effectiveness is fragile in climate-exposed areas. In this context, Bakare et al. (2023) have reported that approximately 98.7% of the sampled farmers were exposed to climate-related shocks emphasizing the vulnerability of agricultural finance in such contexts. The results of the study are aligned with previous research that has shown that though borrowers expose to climate shocks continue to gain positive yield effects, however these gains are substantially smaller compared to unexposed farmers (Carter et al., 2007; Dercon and Christiaensen, 2011; Hill and Viceisza, 2012). Climate shocks through asset losses, recovery constraints, and increases volatility in expected returns weakens credit effectiveness, hence, credit access alone is insufficient to buffer farmers against severe environmental shocks.

## 6. Conclusion

The aim of the study was to identify determinants of microcredit participation and analyze impact of microcredit on cotton and wheat yield among smallholder farmers in Pakistan, along-with a particular emphasis on moderating roles of financial literacy, digital finance adoption, and climate shock exposure. Using probit regression analysis, results indicate that financial literacy, institutional trust, digital finance, farmer education, and off-farm income increases the likelihood of microcredit participation. While results of PSM and moderation analysis reveal that microcredit participation is associated with higher farm productivity. However, this effect is conditional and varies across borrowers' characteristics and contextual factors. The findings of the study advance

the debate on financial inclusion in several meaningful ways. First, it moves beyond average treatment effects by demonstrating the conditional nature of microcredit effectiveness. Second, it identifies financial literacy, digital finance, and climate exposure as central mechanisms influencing productivity outcomes. Third, the findings offer policy-relevant insights, emphasizing the importance of integrated financial inclusion strategies that combine credit access with capability development and risk mitigation. Notwithstanding its contributions, the study has several limitations. First, although propensity score matching reduces selection bias arising from observable characteristics, the possibility of unobserved heterogeneity cannot be completely eliminated. Additionally, the cross-sectional design limits the ability to evaluate long-term of seasonal dynamics. Finally, some variables, including agricultural yields and climate-shock experiences, rely partly on farmers' self-reports and may therefore be subject to measurement error. Future studies employing panel data or experimental approaches could provide stronger evidence regarding the long-term causal effects of microcredit on farm productivity.

Collectively, the findings suggest to maximize microcredit's impact, MFIs and policymakers should develop integrated program that bundle credit with digital skill-building, aligning with initiatives like RAAST and digital Pakistan vision. partner with fintech firms to embed financial literacy modules in loan apps and offer climate-indexed insurance.

**Ethical Statement**

There is no need to obtain permission from the ethics committee for this study.

**Conflicts of Interest**

We declare that there is no conflict of interest between us as the article authors.

**Authorship Contribution Statement**

Concept: Imran, M., Ozcatalbas, O; Design: Imran, M., Tallat, A.; Data Collection or Processing: Imran, M., Kutlar, I., Tallat, A., Statistical Analyses: Imran, M., Tallat, A.; Literature Search: Kutlar, I., Tallat, A.; Writing, Review and Editing: Imran, M., Ozcatalbas, O., Kutlar, I., Tallat, A.

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