Working paper PAK-24003 March 2025

# The role of ultra-poor graduation programmes in building resilience to climate shocks

A mixed-methods investigation in flood-prone Pakistan

**Saima Nawaz**
**Rocco Zizzamia**
**Nasir Iqbal**

DIRECTED BY

FUNDED BY

# The role of ultra-poor graduation programmes in building resilience to climate shocks: A mixed-methods investigation in flood-prone Pakistan

Saima Nawaz* Rocco Zizzamia † Nasir Iqbal‡

March 11, 2025

**Abstract**

This study evaluates the impact of the National Poverty Graduation Programme (NPGP) in Pakistan, particularly its role in enhancing household resilience to climate-induced shocks like floods. Using a mixed-methods approach that combines quantitative data with Regression Discontinuity Design (RDD) and qualitative interviews, we assess the short-term and medium-term effects of asset transfers on household well-being. Our findings reveal that NPGP led to a significant increase in per capita food consumption by PKR 409 (approximately 30% of the mean of the control group) and a 12. 5% increase in the ownership of personal transport (e.g., rickshaws). However, among flood-affected households, livestock assets became a financial liability, leading to increased borrowing, with flood-affected households reporting a 19% higher probability of seeking loans. These results highlight the limited impact of the program on resilience during disasters.

*COMSATS University Islamabad, Pakistan. saima.nawaz@comsats.edu.pk

†University of Oxford, UK rocco.zizzamia@economics.ox.ac.uk

‡Pakistan Institute of Development Economics (PIDE), Pakistan. nasir@pide.org.pk

# 1 Introduction

During the past two decades, poverty graduation programs have emerged as a key strategy to lift the ultra-poor out of poverty by providing a combination of productive assets, skills training, and consumption support (Balboni et al., 2022; Bandiera et al., 2017; Banerjee et al., 2021; Cerkez et al., 2023; Phadera et al., 2019; Edmonds and Theoharides, 2020; Banerjee et al., 2022; Blattman et al., 2020).These programs, often referred to as 'Big Push' interventions, aim to equip beneficiaries with the tools necessary to achieve sustainable livelihoods, thus improving household welfare and facilitating a gradual transition out of poverty (Banerjee et al., 2015; Cerkez et al., 2023; Baird et al., 2024). Although evidence from several countries indicates that such programs can reduce income poverty and improve human capital, there has been limited focus on their potential to build resilience against climate shocks, particularly in flood-prone regions (Banerjee et al., 2015; Cerkez et al., 2023; Baird et al., 2024; Phadera et al., 2019; Nawaz and Iqbal, 2024).

Pakistan, which faces significant economic fragility and vulnerability to climate change (Adnan et al., 2024), offers a unique context in which to study the intersection of poverty alleviation and resilience-building efforts. Pakistan ranks among the top ten nations most affected by extreme weather events, and recurrent flooding continues to disrupt the livelihoods of millions World Bank (2024).[1] In particular in southern regions such as Punjab, where communities are disproportionately exposed to climate shocks, flood events exacerbate poverty, food insecurity, and economic instability (GoP, 2023). In such contexts, poverty graduation programs must not only provide immediate economic relief but also equip households with the resources and adaptive capacity to withstand and recover from shocks (Banerjee et al., 2021; Nawaz and Iqbal, 2024).This dual challenge of poverty alleviation and resilience-building remains under-explored in the literature, highlighting the need for empirical investigations that bridge these two domains (Lake et al., 2023).

The National Poverty Graduation Programme (NPGP) in Pakistan is one of the largest state-led asset transfer programs aimed at empowering the ultra-poor. The program provides beneficiaries with productive assets, such as livestock and small businesses, along with interest-free loans (IFLs) and basic skills training (Nawaz and Iqbal, 2024; Iqbal, 2021). Although the primary objective of the NPGP is to improve household income and socio-economic well-being, it also offers an opportunity to assess how such interventions can influence household resilience in the face of climate shocks. Previous studies on poverty graduation programs, such as Banerjee et al. (2021) in India and Bandiera et al. (2017) in Bangladesh, have documented the economic impacts of asset transfers, but have largely overlooked how these impacts evolve during environmental shocks such as floods (Balboni et al., 2022). Our study seeks to fill this gap by examining how NPGP beneficiaries in flood-prone regions of South Punjab respond to flood shocks and whether the program enhances their ability to adapt and recover.

The research question guiding this study is two-fold: First, we ask whether the NPGP

[1] Floods have become a recurring and devastating natural disaster in Pakistan, increasing intensity over the past few decades. See Appendix Figure A5 for the distribution of natural hazards in the last four decades.

has had a positive impact on household well-being and poverty reduction in flood-prone regions of Pakistan. Second, we investigate whether the assets provided through the program, primarily livestock, serve as a buffer against climate shocks, or if they exacerbate households' vulnerabilities during flood events. This dual focus on both economic outcomes and resilience offers a more holistic assessment of poverty graduation programs, which is necessary to design effective interventions in climate-vulnerable settings.

To answer these questions, we employ a mixed-methods approach, combining a quantitative analysis of household survey data with qualitative interviews with NPGP beneficiaries affected by floods. Using a Regression Discontinuity Design (RDD), we estimate the causal impact of asset transfers on household welfare and adaptive capacity. Qualitative data, collected through semistructured interviews with 148 households, provide rich insights into how beneficiaries experienced both the economic and climatic dimensions of the program. By integrating these methods, our study captures not only the direct economic effects of the NPGP but also the broader socio-environmental context in which these impacts are felt.

Our findings show that, for non-flood-affected households, the NPGP significantly improves household consumption, food security, and asset accumulation. However, the benefits of the program do not extend equally to households affected by floods. For flooded households, asset transfers have limited effectiveness, with no significant improvements in food security, consumption, or asset accumulation. Furthermore, these households experienced increased borrowing to cope with the financial stress caused by flood shocks, highlighting the precarious balance between asset ownership and resilience during crises. These findings suggest that while the NPGP is effective in normal circumstances, its design needs to be strengthened to better support flood-affected households.

This study makes several key contributions to the literature on poverty alleviation and climate resilience. First, it adds to the growing body of evidence on the effectiveness of asset transfer programs to improve household welfare (Banerjee et al., 2015; Balboni et al., 2022; Phadera et al., 2019). Second, it extends this literature by providing empirical evidence on how such programs perform during climate-induced shocks like floods, an area that remains under-explored in existing research. Third, by combining quantitative and qualitative data, this study provides a more nuanced understanding of how households experience the benefits and challenges of asset ownership under varying environmental conditions, contributing to the debate on how to design more resilient poverty alleviation programs (Nawaz and Iqbal, 2024; Edmonds and Theoharides, 2020). Lastly, the use of Regression Discontinuity Design (RDD) provides robust causal estimates of program impact, offering important methodological contributions to the study of development interventions (Cattaneo and Titiunik, 2022).

# 2 The National Poverty Graduation Programme (NPGP) in Pakistan

The National Poverty Graduation Programme (NPGP) is a state-led poverty reduction initiative supported by the International Fund for Agricultural Development (IFAD) and the

Government of Pakistan. The programme focuses on empowering the ultra-poor through a multifaceted "graduation" approach that combines asset transfer, livelihood development, financial inclusion, and social mobilization. The primary objective of NPGP is to allow marginalised households to develop sustainable livelihoods and move out of poverty by providing them with productive assets and training to maximize the utility of these assets. The programme operates with two key components: 1) Poverty Graduation, valued at USD 117.8 million, and 2) Social Mobilization (SM) and Programme Management, worth USD 14.8 million. The first component focuses on the transfer of productive assets and interest-free loans (IFLs) along with training in asset management and financial literacy. The second component includes social mobilization activities aimed at building community resource persons and strengthening community institutions.

A key aspect of the programme is its collaborative approach, involving multiple stakeholders, including the Ministry of Poverty Alleviation and Social Safety (MoPASS), the Government of Pakistan, non-governmental organizations (NGOs), and local communities. The program employs a two-step eligibility process based on the Poverty Score Card (PSC), which assesses the socio-economic status of households. Households with a PSC score below or equal to 16.17 qualify for asset transfer.[2] These households have also been beneficiaries of the Benazir Income Support Programme (BISP), receiving unconditional cash transfers (UCT) to smooth consumption. The NPGP builds on this foundation by providing additional resources in the form of productive assets to ensure sustainable income generation.

In June 2024, the NPGP had reached 324,186 households in 23 districts, providing productive assets to more than 148,225 households and extending interest-free loans to 175,791 households. On average, the value of the asset transfer package (asset plus training of the relevant skill set to use the asset) is PPP USD 1489 (USD 467). The objective of the programme is to graduate at least 50% of the beneficiary households, improve their socioeconomic status, and lift 20% of them from poverty, defined by a PSC score greater than 23. The success of NPGP hinges on the ability of these households to use their transferred assets effectively, thus lifting themselves out of poverty. The most common asset provided are large animals (cow / buffalo), followed by small animals (goats / sheep), loader rickshaws and small businesses / stores (see Appendix Figure A2)

## 2.1 The 2022 Floods in Pakistan: An Overview

Floods have become a recurring and devastating natural disaster in Pakistan, increasing in intensity over the past few decades. The geographic and topographic structure, along with the effects of climate change, have contributed to its high vulnerability to flooding (Rose and Anjum, 2023). The southern regions, particularly in South Punjab, Sindh, and parts of Balochistan, remain the most flood-prone due to their proximity to major river systems such as the Indus River.

[2]The PSC range ($0 < \text{PSC} \leq 16.17$) is consistent with BISP, where the beneficiaries are receiving a consumption support i.e. unconditional cash transfer (UCT) from BISP and will be provided with a tangible productive asset under NPGP. For further details on PMT and PSC see Appendix B

The 2022 floods in Pakistan highlighted the country's extreme vulnerability to climate change, although it contributed less than 1% of global greenhouse gas emissions. With one third of the country submerged, approximately 33 million people were affected and nearly 8 million were displaced.[3] This disaster, unprecedented in scale, exceeded the devastation caused by the 2010 floods. The most significant impacts were felt in already impoverished areas, with vulnerable groups such as women, children, and people with disabilities disproportionately affected. The damage was estimated at USD 14.9 billion, with losses to GDP at USD 15.2 billion. The worst-hit sectors were housing, agriculture, food, livestock, fisheries, and transport. Recovery and reconstruction efforts require an estimated USD 16.3 billion (GoP, 2023). In response to floods, the Federal Government announced Rs 70 billion for flood relief assistance, with 63% of the funds disbursed through BISP. Additionally, the government distributed approximately 600,000 tents, 400,000 tarpaulins, 3.5 million mosquito nets, and nearly 1.8 million food packs (GoP, 2023). As a direct result of the floods, the national poverty rate rose by 3.7 to 4.0 percentage points, causing 8.4 to 9.1 million more people to fall into poverty (GoP, 2022)

# 3 Methods and data

## 3.1 Quantitative data

The assessment is based on numerous unique datasets. First, we used primary survey data, namely *NPGP Household Survey*, collected using a three-stage stratified random sampling technique. We obtained relevant administrative data to develop a sampling framework from NPGP Project Unit, MoPSS, GoP. Administrative data comprise comprehensive details on the targeted households, including their PSC, contact information, intervention details, and the socioeconomic registry (called the National Socio Economic Registry).[4]

To ensure comparability between treatment and control groups, we draw a sample using a fixed bandwidth of 5 as suggested in the literature. This bandwidth is applied to define the groups as follows:

- Treatment group: Consisting of NPGP beneficiaries with PSC scores between 11 and 16.17, denoted as ($11.00 < \text{PSC} \leq 16.17$).
- Control group: Comprising of non-beneficiaries of the program, but with PSC scores just above the eligibility threshold, defined as ($16.17 < \text{PSC} \leq 21.17$).

Based on these administrative data, we developed a three-stage stratified random sampling methodology to select households.
First, the primary sampling units are districts covered under NPGP. We purposely select three districts (DG Khan, Layyah and Jhang) from south Punjab out of 23 districts in Pakistan. Second, we select 9 tehsils from three targeted districts and then select a total of 45

[3]Appendix Figure A3 shows the affected people in the country and the Appendix Figure A4 shows the houses fully or partially damaged during the 2022 flood.

[4]The National Socio-Economic Registry (NSER) BISP develops the NSER and uses to identify beneficiaries for the provision of unconditional cash transfers.

Union Councils (UCs) from the selected tehsils and districts. Union councils were selected based on two criteria: the presence of a control group and a minimum of 20 beneficiaries per union council. Third, from selected UCs, we randomly chose NPGP and/or BISP beneficiary households for the survey in three districts. Keeping in view the program timelines[5], we only considered those NPGP households in sampling framework which received asset transfer before December 2021 to make sure they used the asset for more than a year at the time of the survey.
Primary data collection occurred through a door-to-door survey using a structured questionnaire applying a computer-assisted personal interviewing (CAPI) approach with Android tablets, facilitated through the CSpro platform. The final data set consists of 4,131 households, covering both the treatment (2277 households) and the control groups (1854 beneficiaries of BISP but without NPGP intervention).[6] Field activities including field staff training, pilot assessment of tools, and field survey were carried out from December 2022 to May 2023 in two phases. In phase 1, Jhang and Layyah were covered, while in the second phase, DG Khan was covered.

Second, we used the Pakistan Mouza Census 2020 to capture village-level factors, called MOUZA. The census covers all MOUZAs, which are the smallest administrative units in rural Pakistan, and collects data on land use, crops, irrigation, livestock, forestry and social characteristics of the population[7]. This unique census provides comprehensive pre-intervention information on community-level services available in villages. These include the presence of financial institutions, the state of physical infrastructure, such as roads, and the availability of public utilities, including electricity, water, and other essential facilities. By incorporating these factors, we aim to control for village-level heterogeneity. These data help to control for the impact of these factors in our empirical analysis and improve the accuracy of our results.

[5]PSC baseline survey was conducted in November 2019 and asset transfer started in January 2020

[6]Keeping in view the potential non-response, we initially randomly pick 6,673 households in both the treatment and control groups. Of this total, 3,240 households were in the control group and 3,443 were NPGP beneficiaries of assets. We also randomly draw 57 households who receive assets plus an interest-free loan (IFL) and 1,011 who receive IFL only, but subsequently did not include them in the analysis to keep focus on asset transfers only. We successfully identified and interviewed 5,079 households. Around 520 households were dropped from the final sample due to various reasons like "Death of respondent, Migrated, Refused to interview, Not a beneficiary, Beneficiary not available". During the data cleaning stage, we further excluded 428 households from our analysis which included households that had received IFL from NPGP, those who had never been beneficiaries of the BISP program, households that are not currently receiving BISP payments and some households where data were missing due to issues with the Android application (CSpro).

[7]The Pakistan Bureau of Statistics Agricultural Census Wing conducts a Mauza Census every five years in Pakistan. The census collects essential data on major crops, sources of irrigation, cultivated areas, natural resources and disasters, and the number of settlements in the community suburb. It also covers socio-economic indicators such as the availability of drinking water, electricity, sewerage system, health facilities, education and sports, veterinary hospitals, online credit institutions, and other key information on infrastructure and accessibility to roads, markets, police stations, and social developments. For further details, see https://www.pbs.gov.pk/content/mouza-census-2020

### 3.2 Qualitative data

Our qualitative data collection is designed to complement the quantitative survey by providing in-depth information on the experiences of households affected by floods, particularly those who participate in the NPGP. The qualitative sample was drawn from the 4,131 households that participated in the quantitative survey. Of these, 862 households reported experiencing a flood shock in the last three years. From this subset, we randomly selected 180 households to participate in the qualitative survey. Ultimately, we were able to conduct face-to-face interviews with 148 households (Table 3). The qualitative sampling approach was stratified based on two main criteria: flood exposure and receipt of the NPGP intervention. This stratification ensured that our qualitative sample included households from both the treatment and control groups. This stratified sampling approach allows us to draw comparisons between these two groups and assess how asset transfers influenced household resilience to flood shocks. A comparison of the key characteristics of the qualitative and quantitative samples can be found in Table 4. The table demonstrates that the qualitative sample is broadly representative of the wider survey population in terms of household size, education, and income levels. This representativeness strengthens the validity of the qualitative findings and ensures that they reflect the larger experiences of flood-affected households.

The qualitative interviews were conducted using a semi-structured interview guide. This guide focused on capturing household experiences with flood shocks, their coping strategies, and the role of NPGP assets in recovery and adaptation. The instrument was designed to allow flexibility, enabling interviewers to probe deeply into specific issues that arose during the conversation.

Qualitative data collection was carried out by a team of experienced enumerators who were specifically trained for this study. The enumerators spoke to both male and female household members, ensuring a gender-balanced perspective on household decision-making and coping strategies. The interviews were conducted in local languages, including Punjabi and Saraiki, depending on the preference of the respondent. All interviews were recorded with the consent of the respondents and subsequently transcribed. The interviews were then translated into English and digitised for analysis.

After transcription and translation, qualitative data was coded using a thematic analysis approach. Key themes related to flood impacts, asset usage, and resilience were identified, allowing us to draw out patterns across different households. The analysis aimed to capture the heterogeneity of experiences, particularly in how households perceived the benefits and challenges of NPGP assets under both normal and crisis conditions.

# 4 The role of the NPGP in adaptation to flood shocks – a quantitative perspective

## 4.1 Empirical approach

We used a parametric Regression Discontinuity Design (RDD) to assess the impact of NPGP on various welfare indicators. This strategy provides robust estimates of the causal impact of the NPGP intervention on welfare indicators, addressing potential endogeneity and selection bias issues through the use of the RD framework.[8] The RD approach eliminates selection bias by taking advantage of the discontinuity in eligibility criteria around the eligibility threshold of the program (Thistlethwaite and Campbell, 1960; Lee and Lemieux, 2010). We specify the following model:

$$\mathbf{Y}_i = \alpha + \beta_1 \cdot \mathbf{T}_i + \beta_2 \cdot \mathbf{PSC}_i + \beta_3 \cdot (\mathbf{PSC}_i \cdot \mathbf{T}_i) + \beta_4 \cdot \mathbf{FE}_i + \mathbf{X}_i^\top \cdot \boldsymbol{\gamma} + \mathbf{Z}_i^\top \cdot \boldsymbol{\delta} + \boldsymbol{\epsilon}_i \tag{1}$$

Where: $\mathbf{Y}_i$ represents the outcome variable (welfare measures) for the household $i$; $\alpha$ is the intercept; $\mathbf{T}_i$ is a binary treatment vector indicating the treatment group (1 if $PSC_i \leq 16.17$ and $PSC_i > 16.17$, 0 otherwise) and $\mathbf{PSC}_i$ represents poverty score cards (PSC) for the household $i$. $\beta_1$ represents the causal effect of the NPGP intervention on the welfare indicator. We estimate a separate regression for each outcome variable.

Various covariates are used to capture the demography of household (Card and Giuliano, 2016; Nawaz and Iqbal, 2020; Churchill et al., 2021). $\mathbf{X}_i$ is a matrix that contains covariates for the household $i$ and $\boldsymbol{\gamma}$ represents the vector of coefficients associated with covariates. $\mathbf{FE}_i$ is a vector that represents fixed effects at the district level, capturing district-specific characteristics. $\mathbf{Z}_i$ is a matrix that contains variables at the MOUZA level for the household $i$, providing additional contextual information at the village level, and $\boldsymbol{\delta}$ represents the vector of coefficients associated with variables at the MOUZA level. $\boldsymbol{\epsilon}_i$ is a vector of error terms for the household $i$.

## 4.2 Validity and First Stage

The validity of RD depends on two assumptions: i) the running variable (eligibility index) should be continuous around the cut-off point and ii) households close to the cutoff point should have, on average, similar observed and unobserved characteristics. We use various tests to establish the validity of the proposed identification strategy. First, predetermined characteristics of households are expected to have no discontinuities. We present two types of balance tables: the first focuses on household characteristics and the second on MOUZA-level indicators. We tested for discontinuities in predetermined characteristics of households using RD specification with district-fixed effects. For robustness, we used both 1st and 2nd order polynomial specifications in the RD estimation. The results of both specifications confirm that there are no significant differences between the treatment and control groups

[8] The RD approach is widely used in the literature on impact assessment(Akhtari et al., 2022; Nekoei and Weber, 2017; Pinotti, 2017; Churchill et al., 2021, 2024; Ambler and Brauw, 2024; Asher and Novosad, 2017; Card and Giuliano, 2016; Pinotti, 2017; Adams et al., 2022).

on key indicators (Table 1).[9] We find similar results for the MOUZA variables (Table 2). Both tables show that the sample is well balanced at baseline, which confirms the validity of using RD analysis.

Second, we plot the probability of receiving assets against the PSC score to examine the existence of discontinuity and find strong evidence of discontinuity (Figure 1A). Third, we test the possibility of manipulating the running variable using a histogram and the formal statistical test suggested in the literature (Ambler and Brauw, 2024; Churchill et al., 2024; Adams et al., 2022). The histogram of the running variable (PSC) does not suggest any discontinuity as there is no visible pattern (Figure 1B). We also apply the Cattaneo et al. (2020) test using local polynomial density estimation to check the possibility of manipulation. The Cattaneo et al. (2020) test shows a p-value of 0.406, indicating the absence of manipulation (Figure 2). These results support the use of RD as an empirical strategy.

### 4.3 Results

The results highlight clear differences in the way the asset transfer programme affected beneficiaries who were flooded versus those who were not. The treatment - which was the transference of an asset, led to positive and significant impacts for non-flooded households on several key indicators across well-being, asset accumulation, livestock and financial behaviour. Non-flooded households experienced a strong 1.202 units increase in per capita growth rate (Table 5), with a 0.710 units increase in food security which reflects better access to basic needs.

Asset accumulation and livestock ownership also exhibited strong improvement for NPGP beneficiaries in the non-flooded households. From Table 6, we notice that there were significant impacts on ownership of household items like rickshaws (0.145 unit increase), heaters (8.0 unit increase), refrigerators (27.3 unit increase), and TVs (32.8 unit increase). This, combined with the increase in the likelihood of the ownership of small animals like goats by 0.237 units (Table 7) indicates that not only did these non-flooded households improve their consumption but also accumulated valuable assets- both household and livestock categories. These assets increase the general wealth profile of the household and serve as a way of saving for rural households. In the situation where non-flooded households do not face any consumption shortage or food insecurity, and have better asset profiles now, the households furthered their savings. As detailed in the Table 8, non-flooded NPGP beneficiaries increased their savings by 20% without any significant effects on their borrowing behaviours.

On the other hand, flooded NPGP beneficiaries did not experience similar effects. Although, the PSC growth rate increased by 1.054 units (Table 5), which is less than that for the non-flooded households, the rest of the indicators for the overall well-being show null effects. There is a slight negative effect on food security (-0.493 units) but this effect is not significant. Interestingly, Table 5 and 6 show no effects on any other dimension as well.

[9] We find similar results when we ran RD specifications without fixed effects and variables at MOUZA level.

When compared to the full sample, it seems that flooding reversed any benefits that the asset transfer programme was able to make on the well-being as well as the asset accumulation. Similar results are seen in Table 7 where the only significant improvement for the flooded households is in the ownership and number of goats (0.9 units and 2.778 units respectively). One consideration is that for flooded households small animals like goats are the only way to meet not only their consumption but also their wealth profile, Considering that these are ultra poot, recently flooded households which cannot save (Table 8), it is expected that they would borrow to cope with the damages incurred from the flood. These households increased in their likelihood of borrowing from any source (banks/employers/money lenders/familu/friends/shops) by 52% and by 66% in the last year. There are positive and significant impacts on the amount borrowed with no effects on savings at all. In a broader sense, these households lost their ability to invest in any assets- livestock or household, and on top of that increased their borrowing which led to a reversal of some of the positive effects brought on by the NPGP programme.

# 5 Qualitative evidence

## 5.1 Effects of the NPGP in non-flood periods

Households in the sample received livestock, primarily cows and goats, from the NPGP program, valued between PKR 20,000 and PKR 60,000. These assets were intended to serve as a store of wealth and provide consumption benefits, primarily through milk production. Many households reported using the milk for household consumption and, in some cases, selling surplus to cover basic needs. "We get milk and tea for the household from the cow," one respondent shared. The program enabled households to access immediate nutritional benefits and, in some cases, a modest income stream, thus contributing to their day-to-day welfare.

However, maintaining livestock requires significant resources, and even in normal times, the upkeep costs presented a challenge for many. Fodder, shelter, and veterinary care were recurring expenses that ate into the profits from milk sales. As one respondent remarked, "We have to spend money on feeding the cow, and sometimes the milk isn't enough to cover the costs." Despite these challenges, the assets were generally perceived as beneficial in stable conditions, providing a reliable store of wealth and contributing to household consumption.

When asked whether the assets were worth the costs in everyday settings, households provided mixed responses. While some appreciated the tangible benefits of having livestock, particularly for milk production and occasional sales, others voiced concerns about the cost of maintaining these animals. One respondent shared, "The cow gives us milk, but the expenses are always there, like fodder and care." Overall, while the NPGP assets were seen as helpful during periods of stability, households often weighed the benefits against the ongoing costs of maintenance, finding them beneficial but limited.

Looking ahead, some households expressed cautious optimism about future earnings from the livestock, particularly through the sale of calves or milk. "When the cow gives birth, we will sell the calf and earn some money," one respondent noted. Despite this optimism, concerns over rising costs remained, especially if future environmental shocks like heatwaves occurred. In normal times, households viewed the assets as a safety net with some long-term potential, albeit with significant financial upkeep.

## 5.2 Effects of the NPGP in flood periods

In the context of floods, the benefits of the NPGP assets became far less clear, and, in many cases, the program actually increased households' vulnerability to disasters. The households in the sample are highly exposed to extreme weather events, with most respondents recounting severe floods that damaged homes, crops, and community infrastructure. Floodwaters often inundated fields and homes, destroying essential assets, while livestock frequently became ill or died due to a lack of fodder and shelter. As one respondent explained, "The cow was not giving milk during the flood, and the costs of feeding it kept rising." The program, which had been intended to bolster household resilience, instead became a financial burden during extreme events.

Maintaining livestock during floods presented enormous challenges. Many households found it difficult to secure sufficient fodder for their animals, while others struggled to prevent livestock illness as diseases spread due to poor living conditions. As one respondent noted, "We couldn't get fodder for the cow during the flood, and it became very difficult to manage." These additional costs piled up at a time when households were already facing the loss of crops, homes, and income, further straining their financial situation.

The overall sentiment from respondents was that the assets made them more vulnerable during floods rather than helping them cope. The added costs of maintaining livestock in such challenging conditions were often overwhelming, and many households found that the income from the assets either diminished or stopped altogether during disasters. As one household described, "It made us more vulnerable because we had to spend more to keep the livestock alive during the flood." The livestock, which had been a source of stability in normal times, became a significant financial liability during periods of crisis.

Moreover, households reported that while the assets provided some benefit in stable periods, they became burdensome during disasters, when the costs of maintaining them increased dramatically. This view was common across many respondents who had received livestock through the NPGP program. One respondent stated, "The cow has not brought much benefit during the flood, and the costs have only increased." In contrast to the expected role of building resilience, the asset transfer program often exacerbated the financial strain on households during floods, leaving them less equipped to recover.

In terms of flood preparedness, few households had the means or foresight to take proactive measures. Evacuating livestock or securing homes and assets was difficult due to limited resources and the sudden onset of floods. Most respondents reported that they relied on loans, sold assets, or sought help from relatives to manage the costs incurred during and after the floods. As one respondent explained, "We took loans from relatives and sold household items to cover the immediate expenses." These strategies often left households in deeper financial distress in the long term, as the cost of recovering from the floods far outweighed their ability to prepare.

When asked directly whether the NPGP asset increased their resilience to floods, the overwhelming response was negative. Most households felt that the assets did not help them cope with disaster and, in fact, made them more vulnerable by increasing their financial burden during shocks. "It made us more vulnerable because we had to spend more to keep the livestock alive during the flood," one respondent said. This sentiment was echoed across many households who found that while the asset offered some benefits during normal times, it did not help them build resilience to floods. Instead, the program often added to the challenges households faced in recovering from these shocks.

# 6 Discussion

In a stable environment, the asset (such as livestock) serves two primary functions. First, it acts as a store of value. The asset holds an intrinsic value that can increase over time, especially through reproduction, such as offspring, or through appreciation of its productive potential, for instance, more milk production. The increase in value through producing offspring is high in terms of expected returns, as a new calf or goat could represent a significant addition to the household's wealth. However, this increase is also subject to high variability, as the reproductive success of livestock depends on factors like health, environmental conditions, and care, making the investment inherently risky. Second, the asset generates a flow of income through the production of consumable goods, such as milk or eggs, which can be consumed by the household or sold in the market. This income provides immediate benefits for the household's daily consumption needs, adding a supplementary stream of value.

Maintaining the asset, however, incurs substantial costs. These include regular expenditures on fodder and shelter, necessary to maintain the health and productivity of the livestock. There are also health-related expenses, such as veterinary care, to prevent or treat illnesses. Additionally, there are opportunity costs associated with the time and labor required to manage and care for the asset. In a stable economic environment, the predictable and steady flow of income from other sources allows households to comfortably manage these costs. The balance between the high but risky returns from the asset and the maintenance costs favors asset ownership. The benefits of holding the asset, both as a store of value and as an income generator, typically outweigh the costs, thereby placing the household on a higher consumption equilibrium. This equilibrium represents a state in which households enjoy higher levels of consumption and greater financial security compared to a scenario where they do not own the asset.

In this higher equilibrium, the household benefits from a steady flow of income, such as from milk sales or consumption, which helps to smooth household consumption. There is also the potential for long-term wealth growth through the appreciation of the asset, for example, through the birth of offspring. Moreover, the household enjoys greater financial security and a buffer against moderate fluctuations in income or expenses. This higher consumption equilibrium is sustainable as long as the economic environment remains stable and the costs of maintaining the asset do not rise dramatically.

A flood shock disrupts this equilibrium in two significant ways. First, it decreases the benefits of owning the asset. The income flow decreases because the productivity of the asset, such as milk production, declines due to stress, illness, or lack of fodder, directly reducing the household's income. Furthermore, the expected value of the asset decreases as the likelihood of asset loss, such as the death of livestock due to flood-related illnesses or inability to care for them, increases. This creates greater uncertainty, with a higher risk of total asset loss. Second, the costs associated with the asset spiral upwards. Fodder becomes scarce and expensive, as floods destroy grasslands and feed supplies, driving up the cost of sustaining the livestock. Health risks also increase, as livestock become more susceptible to diseases due to exposure to floodwater, leading to higher veterinary costs. Additionally, damage to shelters makes it harder to care for the animals, exacerbating the problem.

As a result, the benefits of the asset sharply decline while the costs skyrocket, pushing the household toward a precarious financial situation. The household's pre-flood equilibrium is now endangered, and the sharp increase in costs, coupled with the decreased benefits, forces the household to make difficult choices. One option is to liquidate the asset by selling it. This allows the household to smooth consumption in the short term by converting the asset into cash or other resources. However, this decision moves the household back to a lower consumption equilibrium, as they lose the long-term benefits that the asset could potentially provide, such as future income or wealth growth. Alternatively, the household may choose to hold onto the asset, hoping to remain at the higher equilibrium once the flood crisis subsides. However, this strategy involves significant risk. By retaining the asset, the household may face severe short-term consumption reductions, as they continue to allocate scarce resources toward maintaining the asset. This trade-off exposes the household to further financial strain in an already fragile situation.

Households may be reluctant to liquidate a productive asset, given its potential long-term benefits. However, this reluctance can lead to real danger in terms of immediate consumption reductions. The flood shock, by decreasing the asset's benefits and raising its costs, threatens the household's ability to sustain itself in the short term. Thus, while the asset may be valuable in a stable environment, it becomes a burden during times of crisis, complicating the household's ability to cope with shocks and potentially pushing it back into economic precarity.

# 7 Conclusion

We study the impact of Pakistan's largest state-led asset transfer program in the context of a flood-prone country, comparing households that experienced flooding to those that did not. From the literature, we know that asset transfer programs lead to increased consumption, improved well-being, and help families escape poverty by providing additional consumption and income sources. Our study adds to this literature but highlights that in regions prone to extreme climatic conditions and floods, the benefits of asset transfers can be difficult to sustain over time. Floods tend to erode these gains, sometimes resulting in a worsening of overall well-being, as maintaining livestock—the asset transferred—in flooded areas increases costs, particularly due to disease outbreaks. In contrast, in non-flooded areas, the program's benefits are sustained, leading to improved well-being, food security, and financial resilience, as beneficiaries save more.

The findings have important implications for policymakers, NGOs, and development practitioners. First, asset transfer programs in flood-prone regions should consider alternative or diversified asset portfolios. Instead of focusing on livestock, which can be expensive to maintain in such environments, future programs could incorporate more climate-resilient assets such as drought-resistant crops, flood-resistant infrastructure, or off-farm income-generating opportunities, reducing economic vulnerability during floods. In addition, asset transfer programs must be complemented by climate resilience interventions such as investments in flood defenses, water management systems, and veterinary services to manage disease outbreaks. Financial products like microinsurance, specifically designed for climate shocks, could further mitigate the long-term impact of disasters on program beneficiaries.

# References


Adams, A., Kluender, R., Mahoney, N., Wang, J., Wong, F., and Yin, W. (2022). The impact of financial assistance programs on health care utilization: Evidence from kaiser permanente. *American Economic Review: Insights*, 4(3):389–407.

Adnan, M., Xiao, B., Bibi, S., Xiao, P., Zhao, P., and Wang, H. (2024). Addressing current climate issues in pakistan: an opportunity for a sustainable future. *Environmental Challenges*, page 100887.

Akhtari, M., Moreira, D., and Trucco, L. (2022). Political turnover, bureaucratic turnover, and the quality of public services. *American Economic Review*, 112(2):442–493.

Ambler, K. and Brauw, A. d. (2024). Cash transfers and women's agency: Evidence from pakistan's bisp program. *Economic Development and Cultural Change*, 72(3):1117–1150.

Asher, S. and Novosad, P. (2017). Politics and local economic growth: Evidence from india. *American Economic Journal: Applied Economics*, 9(1):229–273.

Baird, S., McIntosh, C., Özler, B., and Pape, U. (2024). Asset transfers and anti-poverty programs: Experimental evidence from tanzania. *Journal of Development Economics*, 166:103182.

Balboni, C., Bandiera, O., Burgess, R., Ghatak, M., and Heil, A. (2022). Why do people stay poor? *The Quarterly Journal of Economics*, 137(2):785–844.

Bandiera, O., Burgess, R., Das, N., Gulesci, S., Rasul, I., and Sulaiman, M. (2017). Labor markets and poverty in village economies. *The Quarterly Journal of Economics*, 132(2):811–870.

Banerjee, A., Duflo, E., Goldberg, N., Karlan, D., Osei, R., Parienté, W., Shapiro, J., Thuysbaert, B., and Udry, C. (2015). A multifaceted program causes lasting progress for the very poor: Evidence from six countries. *Science*, 348(6236):1260799.

Banerjee, A., Duflo, E., and Sharma, G. (2021). Long-term effects of the targeting the ultra poor program. *American Economic Review: Insights*, 3(4):471–486.

Banerjee, A., Karlan, D., Osei, R., Trachtman, H., and Udry, C. (2022). Unpacking a multifaceted program to build sustainable income for the very poor. *Journal of Development Economics*, 155:102781.

Blattman, C., Fiala, N., and Martinez, S. (2020). The long-term impacts of grants on poverty: Nine-year evidence from uganda's youth opportunities program. *American Economic Review: Insights*, 2(3):287–304.

Card, D. and Giuliano, L. (2016). Can tracking raise the test scores of high-ability minority students? *American Economic Review*, 106(10):2783–2816.

Cattaneo, M. D., Jansson, M., and Ma, X. (2018). Manipulation testing based on density discontinuity. *The Stata Journal*, 18(1):234–261.

Cattaneo, M. D., Jansson, M., and Ma, X. (2020). Simple local polynomial density estimators. *Journal of the American Statistical Association*, 115(531):1449–1455.

Cattaneo, M. D. and Titiunik, R. (2022). Regression discontinuity designs. *Annual Review of Economics*, 14:821–851.

Cerkez, N., Khan, A. Q., Rasul, I., and Shoaib, A. (2023). Big push pro-poor policies and economic preferences: Evidence from a partial population experiment. *Working Paper, University College London, UK*. Accessed: 2023-09-11.

Churchill, S. A., Iqbal, N., Nawaz, S., and Yew, S. L. (2021). Unconditional cash transfers, child labour and education: theory and evidence. *Journal of Economic Behavior & Organization*, 186:437–457.

Churchill, S. A., Iqbal, N., Nawaz, S., and Yew, S. L. (2024). Do unconditional cash transfers increase fertility? lessons from a large-scale program. *Economic Inquiry*, 62(1):74–96.

Edmonds, E. and Theoharides, C. (2020). The short term impact of a productive asset transfer in families with child labor: Experimental evidence from the philippines. *Journal of Development Economics*, 146:102486.

GoP (2022). Pakistan floods 2022: Post-disaster needs assessment. Ministry of Planning Development Special Initiatives, Government of Pakistan, Islamabad, Pakistan: https://www.pc.gov.pk/uploads/downloads/PDNA-2022.pdf. Accessed on 2024-10-06.

GoP (2023). Economics survey of pakistan 2022-23: Annexure - iii pakistan floods 2022 impact assessment. Ministry of Finance, Government of Pakistan, Islamabad, Pakistan. https://finance.gov.pk/survey/chapters_23/Annex_III_Pakistan_Floods_2022.pdf. Accessed: 2024-10-06.

Iqbal, N. (2021). Assessing impact of macroeconomic shifts on micro-economy of pakistan's poor and ultra-poor households. *Pakistan Poverty Alleviation Fund, Government of Pakistan*.

Lake, M., Pierotti, R. S., and Alik-Lagrange, A. (2023). Resilience, vulnerability, and social isolation: barriers to poverty reduction in war. *International Studies Quarterly*, 67(4):sqad075.

Lee, D. S. and Lemieux, T. (2010). Regression discontinuity designs in economics. *Journal of economic literature*, 48(2):281–355.

Nawaz, S. and Iqbal, N. (2020). The impact of unconditional cash transfer on fuel choices among ultra-poor in pakistan: quasi-experimental evidence from the benazir income support program. *Energy Policy*, 142:111535.

Nawaz, S. and Iqbal, N. (2024). The power of assets: A catalyst for multidimensional well-being. *SSRN Electronic*.

Nekoei, A. and Weber, A. (2017). Does extending unemployment benefits improve job quality? *American Economic Review*, 107(2):527–561.

OCHA (2022). Pakistan - 2022 Monsoon Floods: Houses Fully and Partially Damaged. UN Office for the Coordination of Humanitarian Affairs (OCHA) https://reliefweb.int/map/pakistan/pakistan-2022-monsoon-floods-houses-fully-and-partially-damaged-22-september-2022. Accessed: 2024-09-30.

Phadera, L., Michelson, H., Winter-Nelson, A., and Goldsmith, P. (2019). Do asset transfers build household resilience? *Journal of Development Economics*, 138:205–227.

Pinotti, P. (2017). Clicking on heaven's door: The effect of immigrant legalization on crime. *American Economic Review*, 107(1):138–168.

Rose, S. and Anjum, A. (2023). Rain rain go away: A snapshot of the flood 2022 and way forward. *The Pakistan Development Review*, 62(3):437–444.

Thistlethwaite, D. L. and Campbell, D. T. (1960). Regression-discontinuity analysis: An alternative to the ex post facto experiment. *Journal of Educational psychology*, 51(6):309.

USAID (2022). Pakistan – Floods: Fact Sheet No. 1. United States Agency for International Development (USAID): https://www.usaid.gov/sites/default/files/2022-12/2022-09-02-USAID-BHA_Pakistan_Floods_Fact_Sheet_1.pdf. Accessed on 2024-10-06.

World Bank (2024). Poverty and Inequality Platform.

Table 1: Balance Test: Household demographic indicators

| | Household | Head characteristics | | |
|---|---|---|---|---|
| | Size | Age | Sex | Literate |
| 1st Order | 0.409 | 6.865 | -0.039 | 0.084 |
| | (1.003) | (4.231) | (0.091) | (0.112) |
| | 0.686 | 0.112 | 0.669 | 0.458 |
| 2nd Order | -4.815 | 11.572 | 0.402 | -0.178 |
| | (3.362) | (12.749) | (0.397) | (0.472) |
| | 0.160 | 0.369 | 0.316 | 0.708 |
| Control Group Mean | 7.13 | 51.58 | 0.87 | 0.22 |
| Treatment Group Mean | 7.48 | 49.76 | 0.84 | 0.20 |
| Observations | 4,131 | 4,131 | 4,131 | 4,131 |
| Distt FE | Yes | Yes | Yes | Yes |

*Note:* Parametric regression discontinuity estimates are reported. We use a global first-order and second-order polynomials in the running variable (PSC). Household Size represents the number of individuals in the household. Age of the head is a continuous variable in years. Gender of Head is a binary variable where Male=1. Literacy of Head is a binary variable that indicates whether the head of the household is literate (literate = 1). The standard errors clustered at the UC level (PSU). *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2: Balance Test: Pre Treatment MOUZA level indicators

| | Health | Electricity | Boys Edu Ins | Girls Edu Ins | Media | Credit facility | Road | Street |
|---|---|---|---|---|---|---|---|---|
| 1st Order | -0.014 | -0.012 | -0.189 | -0.247 | -0.166 | 0.082 | -0.081 | -0.021 |
| | (0.279) | (0.184) | (0.157) | (0.201) | (0.254) | (0.119) | (0.171) | (0.165) |
| | 0.959 | 0.949 | 0.237 | 0.226 | 0.518 | 0.496 | 0.639 | 0.898 |
| 2nd Order | 0.472 | -0.883 | -0.162 | 0.159 | -0.482 | 0.881 | 0.211 | -0.418 |
| | (0.777) | (0.581) | (0.460) | (0.568) | (0.725) | (0.548) | (0.413) | (0.696) |
| | 0.547 | 0.136 | 0.727 | 0.782 | 0.510 | 0.115 | 0.611 | 0.551 |
| Control Group Mean | 0.01 | 0.85 | 0.00 | 0.00 | 0.07 | -0.02 | 0.88 | 0.52 |
| Treatment Group Mean | -0.01 | 0.88 | -0.00 | -0.00 | -0.06 | 0.02 | 0.89 | 0.53 |
| Observations | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 |
| Distt FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Note:* Parametric regression discontinuity estimates are reported. We use a global first-order and second-order polynomials in the running variable (PSC). MOUZA variables include: access to health facilities, access to electricity, educational institutions for boys, educational institutions for girls, access to media, access to credit sources, access to metal road, and access to cemented street. For further details, see Appendix Table A1. The standard errors clustered at the UC level (PSU). *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Attrition Analysis: Qualitative Survey

| **Interview Type** | **Sample Drawn** | **Completed** | **Attrition Rate (%)** |
|---|---|---|---|
| Qualitative Interviews | 180 | 148 | 17.78% |

Table 4: Sample Means: Qualitative Sample Compared to NPGP Household Survey

| | Mean/s.d (NPGP Survey) | Mean/s.d (Qualitative Survey) |
|---|---|---|
| Household Size | 7.323 | 8.503 |
| | (2.988) | (4.028) |
| Household head is female | 0.850 | 0.953 |
| | (0.357) | (0.213) |
| Average total monthly income | 25224.868 | 17267.606 |
| | (11092.723) | (11716.458) |
| Household owns land (agricultural or non-agricultural) | 0.293 | 0.845 |
| | (0.455) | (0.364) |
| Observations | 4131 | 148 |

Table 5: Impact on Overall Well-being

| | PSC | Per Capita Consumption | | | | | | | Food Security |
|---|---|---|---|---|---|---|---|---|---|
| | Growth Rate | Total | Food | Education | Health | Utility | Clothing | Others | Index |
| Full | 1.137*** | 677.932 | 407.509** | -46.488 | 45.376 | 168.000* | 127.633 | 103.280 | 0.487* |
| | (0.182) | (686.208) | (200.305) | (83.481) | (144.519) | (93.168) | (99.939) | (104.552) | (0.271) |
| Control Dep. Var. Mean | 0.29 | 4,118.16 | 1,384.46 | 212.22 | 363.38 | 259.10 | 252.42 | 250.88 | -0.01 |
| Observations | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 |
| Flooded | 1.054** | -91.034 | 410.141 | -201.385 | -181.027 | 8.274 | 7.147 | 191.217 | -0.493 |
| | (0.436) | (1031.642) | (492.558) | (208.078) | (466.380) | (157.198) | (254.884) | (205.196) | (0.478) |
| Control Dep. Var. Mean | 0.24 | 4,548.13 | 1,382.81 | 237.36 | 473.68 | 335.08 | 315.29 | 256.33 | -0.11 |
| Observations | 862 | 862 | 862 | 862 | 862 | 862 | 862 | 862 | 862 |
| Non-Flooded | 1.202*** | 697.386 | 361.247 | -21.668 | 9.645 | 157.333 | 128.164 | 81.194 | 0.710** |
| | (0.204) | (782.695) | (217.733) | (82.758) | (110.093) | (107.423) | (120.224) | (121.587) | (0.336) |
| Control Dep. Var. Mean | 0.30 | 4,008.77 | 1,384.87 | 205.83 | 335.32 | 239.77 | 236.43 | 249.50 | 0.02 |
| Observations | 3,269 | 3,269 | 3,269 | 3,269 | 3,269 | 3,269 | 3,269 | 3,269 | 3,269 |
| Household Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Distt FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| MOUZA | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Note:* Parametric regression discontinuity estimates are reported. To calculate endline PSC, we use the same formula (weights) as used by the government for baseline PSC. The growth rate of PSC is calculated as $\left(\frac{\text{Endline PSC}-\text{Baseline PSC}}{\text{Baseline PSC}}\right)$. Per capita consumption is measured in PKR across different categories (self-reported consumption). The food security index is constructed using the Anderson method [ICW_INDEX], which involves standardizing and centering variables before computing the index based on the inverse covariance matrix [see appendix table **??** for further details on food security index components]. Household controls include: Household Size representing the number of individuals in the household, Head Age as a continuous variable in years, Head Gender as a binary variable where Male = 1, Head Literacy as a binary variable indicating whether the head of the household is literate (Literate = 1) and Employment as a binary variable representing whether the head of the household is employed (Employed=1). District dummies are used to capture district fixed effects. MOUZA variables include: access to health facilities (dummy), access to electricity (dummy), educational institutions for boys (index), educational institutions for girls (index), access to media (index), access to credit sources (index), access to metal road (dummy) and access to cemented street (dummy). Standard errors are clustered at the UC level (PSU). *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

## Table 6: Impact on Asset Accumulation

| | Asset | In Possession | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Index | Car | Motorcyle/Cycle | Rickshaw | Heater | Washing Machine | Fan | Cooking Stove | Refrigerator | TV | Mobile |
| Full | 0.265** | 0.009 | -0.014 | 0.125** | 0.061* | -0.003 | 0.111 | -0.055 | 0.153* | 0.193* | 0.079 |
| | (0.109) | (0.024) | (0.112) | (0.060) | (0.031) | (0.135) | (0.087) | (0.079) | (0.081) | (0.108) | (0.099) |
| Control Dep. Var. Mean | -0.01 | 0.01 | 0.08 | 0.02 | 0.01 | 0.15 | 0.85 | 0.08 | 0.13 | 0.22 | 0.83 |
| Observations | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 |
| Flooded | -0.005 | -0.044 | -0.068 | 0.069 | -0.019 | -0.008 | 0.010 | 0.251 | -0.291 | -0.250 | 0.185 |
| | (0.299) | (0.075) | (0.233) | (0.142) | (0.045) | (0.231) | (0.191) | (0.182) | (0.181) | (0.275) | (0.150) |
| Control Dep. Var. Mean | -0.01 | 0.01 | 0.08 | 0.02 | 0.01 | 0.15 | 0.85 | 0.08 | 0.13 | 0.22 | 0.83 |
| Observations | 862 | 862 | 862 | 862 | 862 | 862 | 862 | 862 | 862 | 862 | 862 |
| Non-Flooded | 0.360** | 0.025 | 0.011 | 0.145** | 0.080** | 0.024 | 0.161 | -0.110 | 0.273** | 0.328*** | 0.024 |
| | (0.142) | (0.030) | (0.134) | (0.062) | (0.035) | (0.152) | (0.102) | (0.091) | (0.110) | (0.120) | (0.113) |
| Control Dep. Var. Mean | -0.01 | 0.01 | 0.08 | 0.02 | 0.01 | 0.15 | 0.85 | 0.08 | 0.13 | 0.22 | 0.83 |
| Observations | 3,269 | 3,269 | 3,269 | 3,269 | 3,269 | 3,269 | 3,269 | 3,269 | 3,269 | 3,269 | 3,269 |
| Household Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Distt FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| MOUZA | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Note:* Parametric regression discontinuity estimates are reported. Asset index is constructed using Anderson method [ICW_INDEX],which involves standardizing and centering variables before computing the index based on the inverse covariance matrix. Household controls include: Household Size representing the number of individuals in the household, Head Age as a continuous variable in years, Head Gender as a binary variable where Male = 1, Head Literacy as a binary variable indicating whether the head of the household is literate (Literate = 1) and Employment as a binary variable representing whether the head of the household is employed (Employed=1). District dummies are used to capture district fixed effects. MOUZA variables include: access to health facilities (dummy), access to electricity (dummy), educational institutions for boys (index), educational institutions for girls (index), access to media (index), access to credit sources (index), access to metal road (dummy) and access to cemented street (dummy). Standard errors are clustered at the UC level (PSU). *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

## Table 7: Impact on Livestock

| | Livestock | | Cow | | Goat | | Camel | | Poultry | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Own | Quantity | Own | Quantity | Own | Quantity | Own | Quantity | Own | Quantity |
| Full | 0.346* | 0.196 | 0.307 | 0.179 | 0.371*** | 0.929** | -0.016 | 0.021 | 0.067 | -0.044 |
| | (0.200) | (0.207) | (0.191) | (0.409) | (0.124) | (0.373) | (0.041) | (0.063) | (0.144) | (0.564) |
| | 0.091 | 0.349 | 0.115 | 0.664 | 0.005 | 0.017 | 0.705 | 0.741 | 0.642 | 0.937 |
| Control Group Mean | -0.08 | -0.07 | 0.38 | 0.64 | 0.28 | 0.59 | 0.03 | 0.03 | 0.21 | 0.61 |
| Treatment Group Mean | 0.06 | 0.05 | 0.68 | 1.12 | 0.28 | 0.73 | 0.02 | 0.02 | 0.20 | 0.58 |
| Observations | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 |
| Flooded | 0.691 | 0.433 | 0.357 | -0.284 | 0.900** | 2.778** | 0.042 | 0.042 | 0.015 | 0.303 |
| | (0.485) | (0.490) | (0.454) | (1.340) | (0.392) | (1.068) | (0.065) | (0.065) | (0.253) | (1.329) |
| | 0.165 | 0.385 | 0.438 | 0.834 | 0.030 | 0.015 | 0.523 | 0.523 | 0.952 | 0.821 |
| Control Group Mean | -0.08 | -0.07 | 0.38 | 0.64 | 0.28 | 0.59 | 0.03 | 0.03 | 0.21 | 0.61 |
| Treatment Group Mean | 0.06 | 0.05 | 0.68 | 1.12 | 0.28 | 0.73 | 0.02 | 0.02 | 0.20 | 0.58 |
| Observations | 862 | 862 | 862 | 862 | 862 | 862 | 862 | 862 | 862 | 862 |
| Non-Flooded | 0.249 | 0.122 | 0.304 | 0.287 | 0.237** | 0.500 | -0.031 | 0.013 | 0.058 | -0.230 |
| | (0.211) | (0.228) | (0.198) | (0.436) | (0.114) | (0.407) | (0.049) | (0.075) | (0.145) | (0.582) |
| | 0.245 | 0.595 | 0.132 | 0.515 | 0.043 | 0.226 | 0.532 | 0.859 | 0.691 | 0.695 |
| Control Group Mean | -0.08 | -0.07 | 0.38 | 0.64 | 0.28 | 0.59 | 0.03 | 0.03 | 0.21 | 0.61 |
| Treatment Group Mean | 0.06 | 0.05 | 0.68 | 1.12 | 0.28 | 0.73 | 0.02 | 0.02 | 0.20 | 0.58 |
| Observations | 3,269 | 3,269 | 3,269 | 3,269 | 3,269 | 3,269 | 3,269 | 3,269 | 3,269 | 3,269 |
| Household Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Distt FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| MOUZA | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

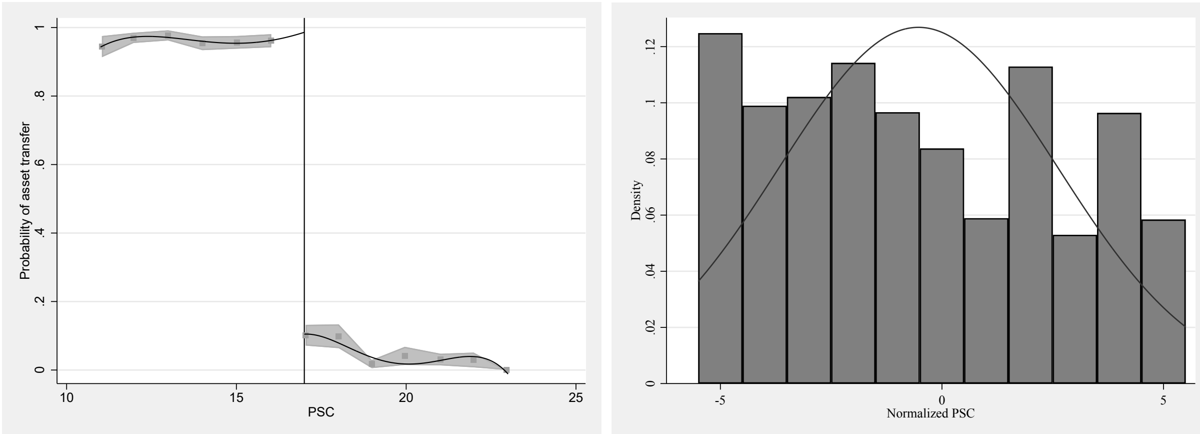
*Note:* Household controls include: Household Size representing the number of individuals in the household, Head Age as a continuous variable in years, Head Gender as a binary variable where Male = 1, Head Literacy as a binary variable indicating whether the head of the household is literate (Literate = 1) and Employment as a binary variable representing whether the head of the household is employed (Employed=1). District dummies are used to capture district fixed effects. MOUZA variables include: access to health facilities (dummy), access to electricity (dummy), educational institutions for boys (index), educational institutions for girls (index), access to media (index), access to credit sources (index), access to metal road (dummy) and access to cemented street (dummy). Standard errors are clustered at the UC level (PSU). *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Impact on Financial Behaviour

| | Borrowing Behaviour | | | | Saving Behaviour | |
|---|---|---|---|---|---|---|
| | Any Source | Number of Sources | In Last Year | Amount (IHS) | Any | Saving Amount (IHS) |
| Full | 0.019 | -0.108 | 0.177 | -0.512 | 0.155 | 0.298 |
| | (0.142) | (0.382) | (0.130) | (1.691) | (0.101) | (0.526) |
| | 0.893 | 0.779 | 0.180 | 0.764 | 0.134 | 0.574 |
| Control Dep. Var. Mean | 0.47 | 0.79 | 0.35 | 5.34 | 0.08 | 0.37 |
| Observations | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 | 4,131 |
| Flooded | 0.525* | 0.348 | 0.665** | 5.569* | -0.016 | -1.221 |
| | (0.295) | (0.709) | (0.314) | (3.203) | (0.170) | (0.891) |
| | 0.086 | 0.628 | 0.044 | 0.094 | 0.926 | 0.182 |
| Control Dep. Var. Mean | 0.47 | 0.79 | 0.35 | 5.34 | 0.08 | 0.37 |
| Observations | 862 | 862 | 862 | 862 | 862 | 862 |
| Non-Flooded | -0.108 | -0.204 | 0.061 | -2.000 | 0.205* | 0.731 |
| | (0.145) | (0.416) | (0.146) | (1.722) | (0.107) | (0.644) |
| | 0.460 | 0.627 | 0.678 | 0.252 | 0.063 | 0.263 |
| Control Dep. Var. Mean | 0.47 | 0.79 | 0.35 | 5.34 | 0.08 | 0.37 |
| Observations | 3,269 | 3,269 | 3,269 | 3,269 | 3,269 | 3,269 |
| Household Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Distt FE | Yes | Yes | Yes | Yes | Yes | Yes |
| MOUZA | Yes | Yes | Yes | Yes | Yes | Yes |

*Note:* Household controls include: Household Size representing the number of individuals in the household, Head Age as a continuous variable in years, Head Gender as a binary variable where Male = 1, Head Literacy as a binary variable indicating whether the head of the household is literate (Literate = 1) and Employment as a binary variable representing whether the head of the household is employed (Employed=1). District dummies are used to capture district fixed effects. MOUZA variables include: access to health facilities (dummy), access to electricity (dummy), educational institutions for boys (index), educational institutions for girls (index), access to media (index), access to credit sources (index), access to metal road (dummy) and access to cemented street (dummy). Standard errors are clustered at the UC level (PSU). *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure 1: First Stage RD Plot and Histogram

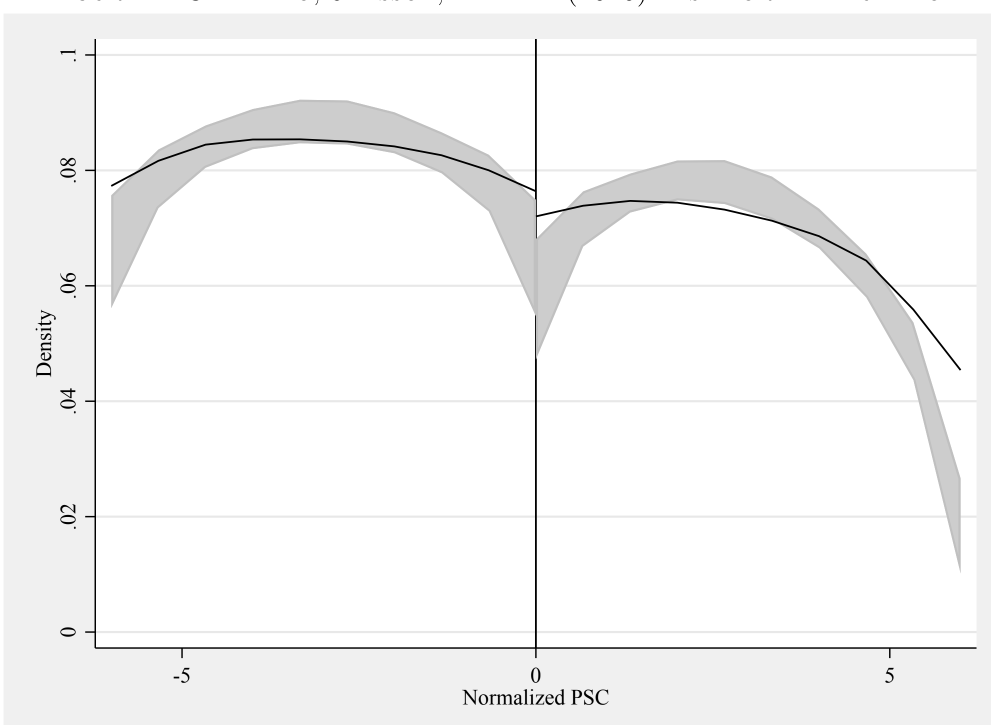



A: RD Plot of STATUS and Normalized PSC

B: Histogram of Normalized PSC

Notes: Figure A displays the RD Plot of STATUS and PSC (normalized) using "rdplot" STATA command. The shaded area represents a confidence interval 95%. The probability of asset transfer is plotted against the normalized PSC. Figure B shows the PSC histogram (normalized) for discrete data, which illustrates the density of data within the range [-5, 5].

Figure 2: Cattaneo, Jansson, and Ma (2020) test for manipulation



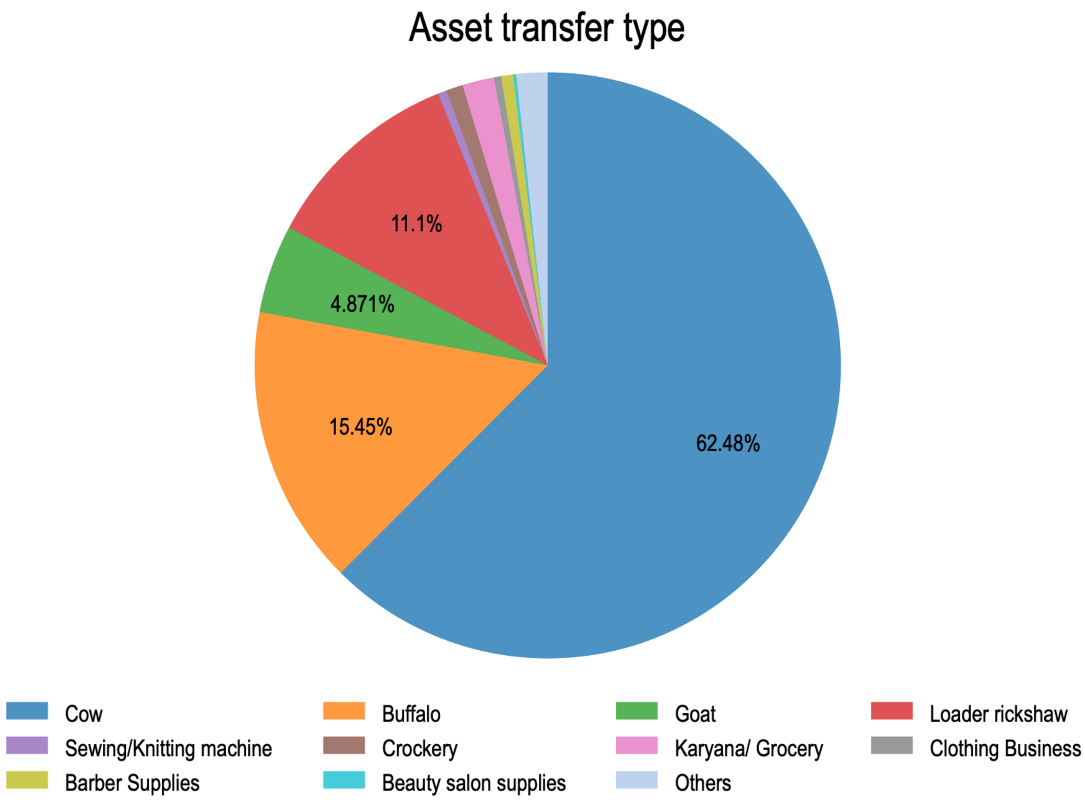

Notes: The figure shows the Local Polynomial Density Estimator proposed in Cattaneo et al. (2020). The local polynomial density estimate (solid black) and robust bias-corrected confidence intervals (shaded grey) are computed using the STATA package described in Cattaneo et al. (2018). The p-value for the test of smoothness of the running variable around the cut-off is 0.406.

# A Appendix

Appendix Figure A1: District Coverage

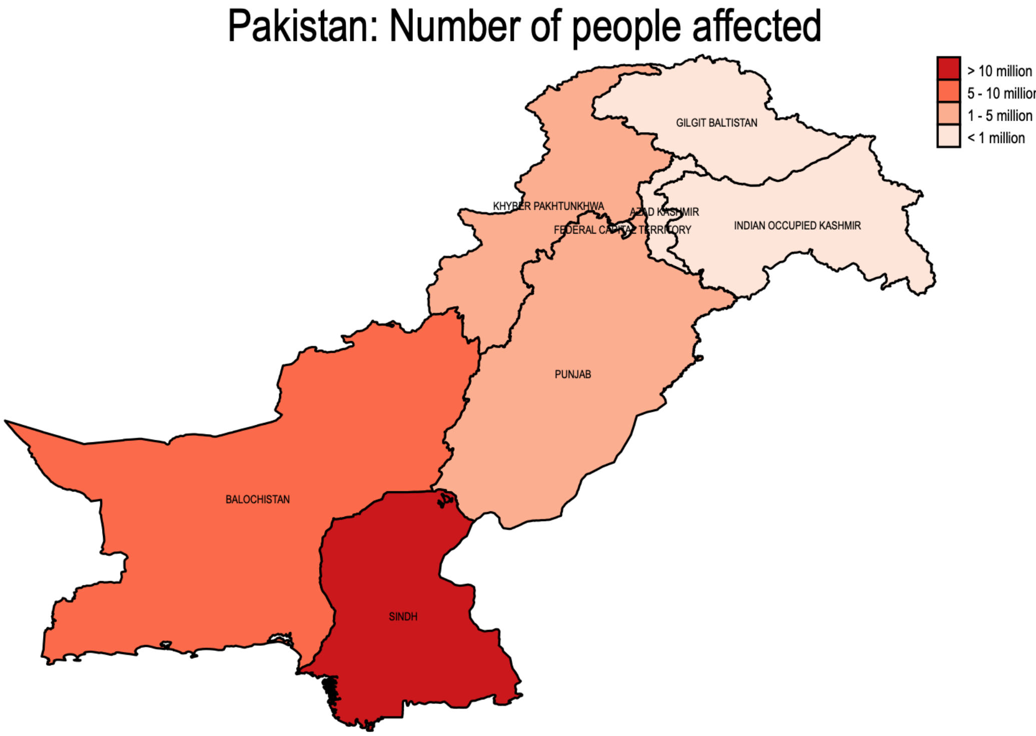

Notes: Author's formulation.Present districts cover from Punjab.

Appendix Figure A2: Percentage distribution of assets



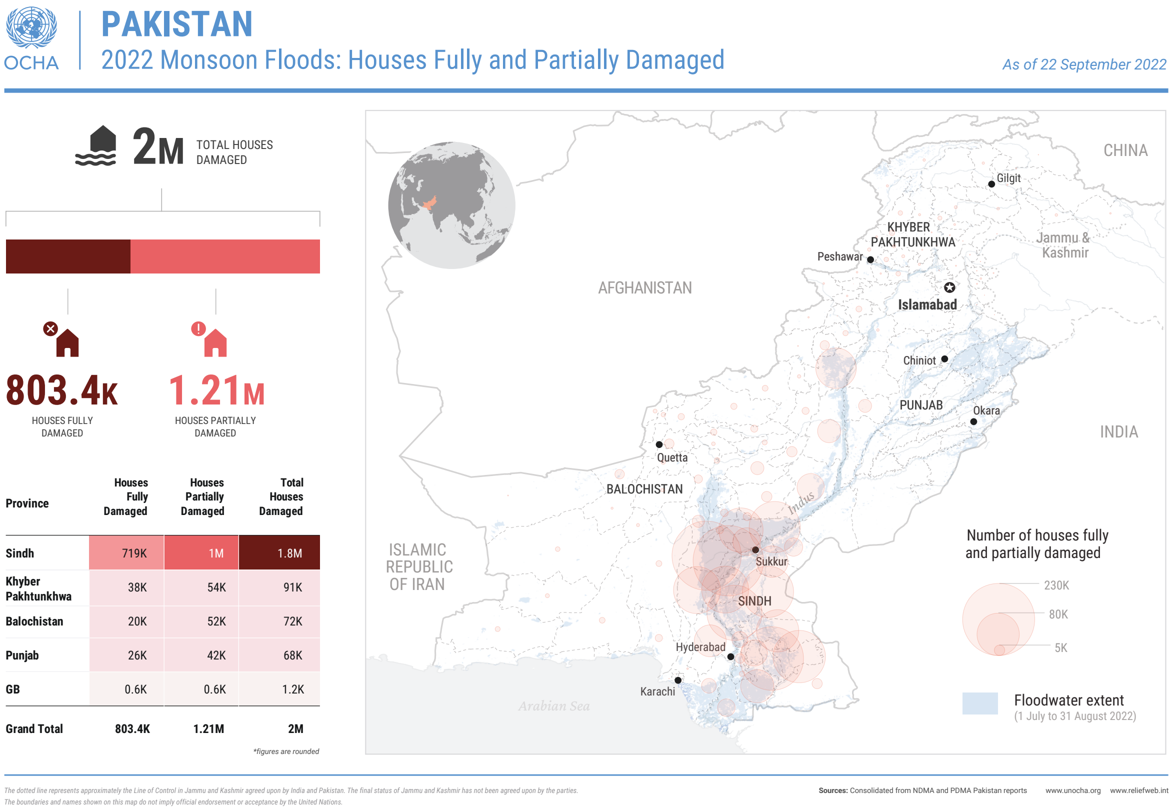

Notes: Author's formulation based on Survey data.

Appendix Figure A3: Number of People Affected Due to Flood Across Pakistan




Source: USAID (2022) Notes: Will add.

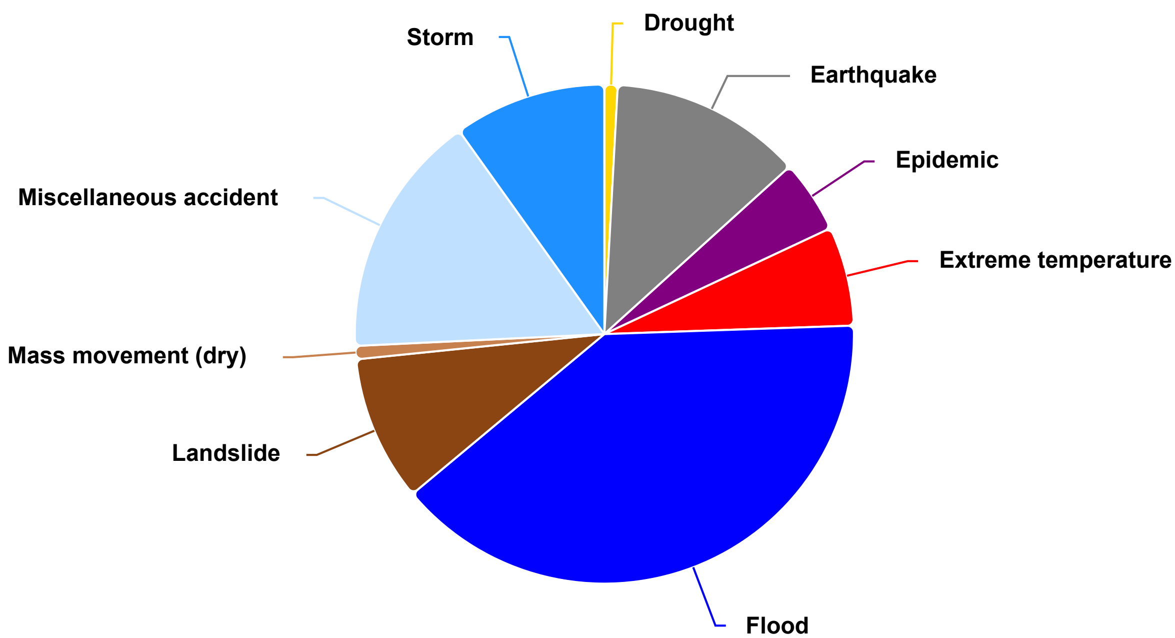
Appendix Figure A4: Pakistan - 2022 Monsoon Floods: Houses Fully and Partially Damaged




| Province | Houses Fully Damaged | Houses Partially Damaged | Total Houses Damaged |
|---|---|---|---|
| Sindh | 719K | 1M | 1.8M |
| Khyber Pakhtunkhwa | 38K | 54K | 91K |
| Balochistan | 20K | 52K | 72K |
| Punjab | 26K | 42K | 68K |
| GB | 0.6K | 0.6K | 1.2K |
| Grand Total | 803.4K | 1.21M | 2M |

Source: OCHA (2022)
Notes: Houses fully and partially damaged as of 22 September 2022.

Appendix Figure A5: Pakistan: Average Annual Natural Hazard Occurence for 1980- 2022




Source: World Bank (2024)

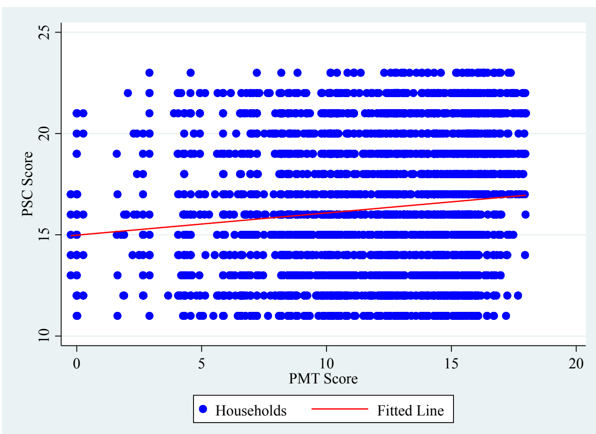
# B Details on PMT and PSC

The Proxy Means Test (PMT) and Poverty Scorecard (PSC) are two scores used to identify poverty levels and determine eligibility for social programmes such as BISP and NPGP. The PMT, applied by the BISP, measures the economic welfare of households using a set of 23 indicators, focusing on characteristics such as the number of dependents, educational attainment, asset ownership, and housing conditions. It uses data from the Pakistan Social and Living Standards Measurement Survey (PSLM) and applies a linear regression model with monthly household expenditures as the dependent variable. The PMT includes key indicators such as the number of dependents, educational level of the household head, asset ownership (e.g., refrigerators, vehicles), agricultural land ownership, and housing conditions. Based on these indicators, PMT generates a score between 0 and 100, with households scoring below 16.17 deemed eligible for BISP benefits.

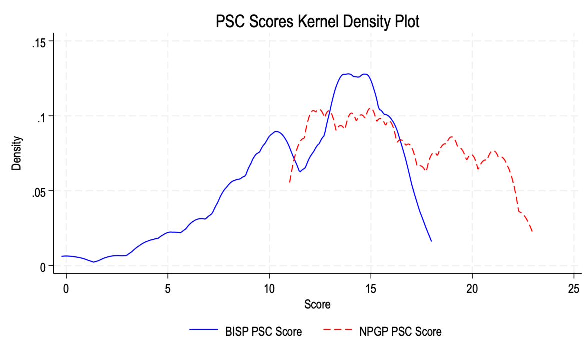
In contrast, the Poverty Scorecard (PSC) used in the NPGP employs a similar approach but focuses on a slightly different set of variables. The PSC comprises 13 indicators, centring on household size, age distribution, education, and ownership of specific assets like livestock and vehicles. The PSC captures variables such as household size and age distribution, educational attainment of the household head, and asset ownership (e.g., TV, cooking appliances, air conditioners). It also assigns a score ranging from 0 to 100, with the same eligibility threshold of 16.17 used to determine eligibility for the NPGP asset transfer programme.

Although both PMT and PSC serve the same purpose of identifying ultra-poor households, there are notable differences between them. The PMT uses a broader range of 23 indicators, including more detailed questions on asset ownership and education, whereas the PSC focuses on 13 indicators with emphasis on household size, age composition, and select assets. In addition, PMT employs a linear regression model based on household expenditure, while PSC uses a simpler weighted scoring system directly tied to specific assets and educational levels. The figure A6 shows a positive correlation between PMT and PSC scores, indicating that households with higher PMT scores tend to have higher PSC scores as well. The fitted line further highlights this trend, suggesting a consistent relationship between the two scoring methods across households.

Appendix Figure A6: Correlation between PMT and PSC Scores




A: Correlation between PMT and PSC Scores




B: Kernal Density Plot

Notes:

# C Acknowledgment, IRB approval and cross-validation

**IRB approval**: IRB approval was granted by the PIDE Research Ethics Review Committee through the IRB Approval Letter: PIDE/PERC/2024-001 and IRB Approval Letter: PIDE/PERC/2022-001.

**Back checks and cross-validation**: To further ensure data quality, we regularly conducted back checks by calling randomly selecting 10 percent of interviewed households. A project management unit was established at PIDE, headed by PI and supported by Senior Research Associate, to draw random samples on a regular basis and call them accordingly. Any variations in reporting were discussed with the field supervisor on a regular basis.

**Declaration of generative AI and AI-assisted technologies in the writing process** During the preparation of this work, the author(s) used ChatGPT 4 to eliminate grammatical errors. After using this tool/service, the author(s) reviewed and edited the content as needed and takes (s) full responsibility for the content of the publication.

**Acknowledgment** This study was made possible through the collaborative efforts of Pakistan Institute of Development Economics (PIDE), Ministry of Poverty Alleviation and Social Safety, the Government of Pakistan, COMSATS University Islamabad (CUI), and various stakeholders, each contributing significantly to our research work. We express our thanks to the Higher Education Commission (HEC) and the World Bank for their financial support through the Local Challenge Fund (LCF) grant. **The authors express their thanks to the International Growth Center (IGC) for its support in conducting qualitative field interviews under the project PK-24003 titled "Empowering Rural Communities for Climate Change Adaptation: Evaluating the Impact of the National Poverty Graduation Program in South Punjab, Pakistan"** We express our sincere gratitude to the Rural Innovation Hub (Pvt) Limited for their support in conducting qualitative field interviews for this study. The authors thank the NPGP Project Management Unit (PMU) team, which played a vital role in the sharing of administrative data and the facilitation of logistics. The authors acknowledge the cooperation and assistance extended by the management and staff of the National Rural Support Program (NRSP) in Jhang, Layyah, and D.G. Khan. Special thanks go to the dedicated survey team, whose tireless efforts in the field were pivotal in collecting high-quality data essential to the success of this study. We also acknowledge the role that field monitors and supervisors played in ensuring data accuracy and reliability. A heartfelt thank you is extended to the communities and beneficiary families who actively participated in the survey, providing invaluable information. The authors also express their appreciation to the HEC reviewers, whose guidance and support at various stages of the study significantly contributed to its improvement.

Appendix Table A1: Variable Definitions of MOUZA Indicators

| Variable | Definition |
|---|---|
| **HEALTH Index** | Aggregates several health-related facilities, including Population Welfare Centres (PWC), Basic Health Units (BHU), Rural Health Centres (RHC), NGO healthcare, Mother and Childcare Centres (MCC), Private Doctors (PDR), Hospitals with Doctors (HOD), and Female Medical Workers (FMW). Standardized and aggregated using an inverse covariance index. |
| **ELECTRICITY** | Binary variable coded as 1 if electricity is fully available in the MOUZA, 0 otherwise. |
| **EDUCATION (BOYS) Index** | Measures the availability of educational facilities for boys at different levels, including Primary, Middle, High School (HS), College, Vocational Institutions (VI), and Religious Institutions (RI). Standardized and aggregated using an inverse covariance index. |
| **EDUCATION (GIRLS) Index** | Similar to the boys' education index but for girls, capturing the same levels of education. |
| **MEDIA Index** | Reflects access to media outlets such as Radio, Television (TV), Cable, and Newspapers. Standardized and aggregated into a media index for each MOUZA. |
| **CREDIT SOURCES Index** | Includes different credit sources available in the MOUZA, such as ZTBL, Cooperative Banks, Commercial Banks, Microfinance Banks, NGOs, RSPs, Government Sources, Brokers, and Others. Standardized and aggregated into a credit sources index. |
| **ROAD METAL** | Indicates whether roads in the MOUZA are metal-paved (coded as 1 if yes, 0 otherwise). |
| **STREET** | Captures the status of streets in the MOUZA, where 1, 2, or 3 represent different levels of street development or quality, and 0 otherwise. |

theigc.org