Credit, Growth and Resilience: Evidence from Floods in Pakistan

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Abstract

I examine how microcredit affects growth and resilience. While credit can fuel growth and investment, it may also exposes borrowers to heightened risk, making its effect on resilience ambiguous. Focusing on Pakistan's SUCCESS program, I leverage a loan eligibility threshold to show that credit access boosted loan uptake from 1% to 46% among eligible households, spurring a 22% increase in livestock. Yet, this came at the cost of reduced investment in housing quality, leading to greater flood damage and displacements. Exploiting the spatial variation in the intensity of 2022 floods in Pakistan, I find that within highly-flooded villages, loan-eligible households have 24% fewer livestock, deteriorating mental health, and higher rates of loan default after the floods. In contrast, loan-eligible households within low-flooded villages, continue to accumulate livestock, with a gap emerging between loan-eligible households in high- and low-flooded villages over time. These results suggest that in settings with incomplete financial markets, credit access could induce a tradeoff between growth and resilience.

Keywords: Climate, floods, resilience, growth, credit
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1 Introduction

Access to credit for households in low- and middle-income countries has grown substantially over recent decades, largely due to the expansion of microfinance (Convergence, 2019). The primary motivation for improving access to credit is that it can unlock growth and investment (Banerjee and Newman, 1993; Banerjee, 2013). However, the impact of credit on household resilience—referring to households' capacity to manage shocks in ways that mitigate negative impacts on well-being—remains unclear (Béné et al., 2015). While investment and growth can improve resilience over time, they also increase risk exposure, potentially raising vulnerability. Credit's effectiveness in enhancing resilience depends on the availability of opportunities that reduce risk exposure. For example, households may use credit to optimally diversify investments, or they may need credit to overcome a capital hurdle in order to engage in lower-risk activities, such as financing technologies that reduce risk (Emerick et al., 2016; Brooks and Donovan, 2020).

Understanding how credit impacts resilience is becoming increasingly important in the context of climate change. It is estimated that more than 3.6 billion people are exposed to extreme weather shocks (IPCC, 2023). The majority of them are poor, financially constrained, and live in low- and middle-income countries (Rentschler and Salhab, 2020). While credit is gaining traction as a potential tool to improve household resilience to these shocks, there is limited evidence on its effectiveness (Parry et al., 2007).

This paper aims to bridge this gap by examining how access to credit affects both growth and resilience.[1] Addressing this question is challenging, as it requires two essential elements: (a) plausibly exogenous variation in credit access and (b) variation in shock exposure. I overcome these challenges by leveraging a credit access program in Pakistan, where some areas with improved access to credit also endured a severe natural shock. This setting enables me to assess whether credit access fosters growth and resilience in the absence of shocks and, importantly, how these outcomes change when households are exposed to a climate-related shock.

This paper leverages Pakistan's largest women-led development initiative, the Sindh Union Council and Community Economic Strengthening Support (SUCCESS) program. SUCCESS is a multifaceted community-driven program aimed at empowering local communities. The program established community organizations at the neighborhood level and provided them with capital grants to distribute as loans to their members. Between 2018 and 2022, this

[1]Resilience and growth can complement each other. For example, the use of flood-resistant seeds has been shown to reduce risk while increasing productivity (Emerick et al., 2016). However, there may also be a trade-off when individuals underinvest in risky but potentially profitable opportunities (Karlan et al., 2014)

program mobilized over 600,000 rural women into community organizations and provided over 4 billion PKR (approximately \$14 million) in interest free loans to 100,000 ultra-poor, landless women with no prior access to formal credit (Fazal Ali Saadi, 2022).

The setting of this study is rural Sindh, a province of Pakistan. Pakistan, in general, and Sindh, in particular, are vulnerable to natural shocks. Pakistan ranks among the top 10 countries most vulnerable to natural shocks and is 5th in terms of flood vulnerability (Rentschler and Salhab, 2020). In 2022, Pakistan received unprecedented rainfall. As a result, the country experienced one of the worst floods in its history, with one-third of the country submerged in water. These floods affected 33 million people, with 8 million displaced and 20 million people in need of life-saving assistance. Sindh was hardest hit, accounting for over 70% of the damages. Most people in Sindh rely on informal insurance within the village, which is less effective for collective shocks like floods (Udry, 1990; Fafchamps et al., 1998).

To estimate the causal effects of access to credit on growth and resilience, I exploit a discontinuity in loan eligibility. SUCCESS loan eligibility is determined through a poverty score cutoff, motivating the use of a regression discontinuity (RD) framework. The identification assumption is that households around the cutoff are as good as randomly assigned. I test the validity of the RD by verifying that the household characteristics are smooth around the cutoff. To study the impact of pre-flood household investment on resilience, I exploit spatial variation in the intensity of 2022 floods. Given that the floods were driven by heavy rainfall, I classify villages as high- or low-flooded based on the difference between their average rainfall and the rainfall received in 2022. I then employ a difference-in-discontinuities design to analyze the loan versus no-loan discontinuity across high- and low-flooded villages. To collect outcome measures after the floods, I conducted two rounds of surveys in 98 villages. The first survey was conducted immediately after the floods in December 2022, and the second survey was conducted a year later.

I find that there is high demand for credit. From 2018 to 2022, 46% of households eligible for a SUCCESS loan took a loan.[2] Since no other institution offers loans in the area, the overall differential take-up between loan-eligible and loan-ineligible households is also 46%, creating a stronger first stage for establishing the plausibility of effects on downstream outcomes. The take-up of SUCCESS loans does not crowd out other sources of borrowing, such as family or shopkeeper loans, which indicates that people are generally financially constrained. The high take-up is followed by a very low default rate, suggesting that borrowers

[2] The take-up is high compared to the take-up of microcredit programs around the world. Banerjee et al. (2015b) report a take-up rate of 17% to 31% in six RCTs conducted in Bosnia, Ethiopia, India, Mexico, Morocco, and Mongolia. The higher take-up rate in this setting may be attributed to lending to inframarginal borrowers or the low interest rates charged.

are creditworthy.

Next, I assess how households use the increased access to credit. In this setting, people have multiple options available, each with varying risks and returns. People can use the loan amount on income-generating activities such as starting a business, farming or livestock. Livestock, in particular, is a high-return investment in this setting, but also comes with a higher mortality rate during floods.[3] Another important productive investment for households is migration, which could improve both growth and resilience: as most household members work as daily laborers within the village and cannot find work in certain months, credit can enable them to migrate or seek employment in areas that are less flood prone.[4] Moreover, as loan usage is not monitored, households have the option to use it for consumer durables like improved housing or assets. Housing, in particular, carries low risk and could enhance household resilience to floods. However, it is less likely to generate any income. Finally, households may use the loan for non-durable consumption, such as food.

In practice, the increased borrowing resulting from the SUCCESS program leads to an increase in livestock holdings, with no change in business, agriculture, or migration. Compared to loan-ineligible households, loan-eligible households are 6 percentage points more likely to own livestock and have 0.34 (22%) more livestock. This increase, however, crowds out other investments. Loan-eligible households are 0.07 standard deviations less likely to have non-livestock assets, such as mobile phones and TVs. Importantly, loans reduce housing quality relative to the control group, with loan-eligible households experiencing a 0.11 standard deviations drop in the housing quality index compared to loan-ineligible households. This decline is driven by a lower likelihood of having a concrete floor and roof. The reduction of assets and housing quality may seem surprising at first. However, it can be explained by the lumpiness of livestock (Banerjee, 2013). Since the loan amount is insufficient to cover the full cost of a goat, households need to use other funds to supplement their purchase.

I next examine how these investments were affected by the 2022 floods. First, I compare the damages incurred by loan-eligible households relative to loan-ineligible households. Floods wipe out a larger share of livestock among loan-eligible households. Loan-eligible households lose 0.74 livestock (40%), while loan-ineligible households lose 0.46 livestock (30%). Loan-eligible households are also 3.4 percentage points more likely to have a damaged house after the floods, likely due to their lower investment in housing quality prior to the floods. These damages vary by flood intensity, with high-flooded villages accounting for most of the losses. Loan-eligible households are also 5 percentage points more likely to be displaced during the

[3] The average rate of return on livestock is 21% to 30% (Attanasio and Augsburg, 2014), and a mortality rate of 35% during floods.

[4] Bryan et al. (2014) show that credit could motivate households to migrate. There is substantial evidence that migration leads to economic gain (Khandker et al., 2012; Liebensteiner, 2014)

floods. However, by the time we conducted the first survey, these displaced households had already returned to their villages.

Although loan-eligible households suffered greater damages, they might also recover faster. To assess household resilience, I examine multiple post-flood indicators, including livestock and non-livestock assets, repairs undertaken, food security, and mental health. I analyze the loan-eligibility discontinuity separately in high- and low-flooded villages, as the outcomes will vary by flood intensity, and looking at the pooled effects will underestimate the results. Within the high-flooded villages, after a year of floods, loan-eligible households have 24% fewer livestock compared to loan-ineligible households. This reduction is not driven by households selling livestock; instead, it results from livestock dying. Additionally, there is no evidence that loan-eligible households make more repairs to damaged houses. Compared to loan-ineligible households, the mental health of the loan-eligible households in these high-flooded villages has declined by 0.18 standard deviations and remains lower a year after the floods. Likewise, their food insecurity has increased (0.03 standard deviations) but is not statistically significant.

In contrast, loan-eligible households in the low-flooded villages continue to grow and accumulate more livestock. After the floods, loan-eligible households in the low-flooded villages are 9.4 percentage points more likely to own livestock and have 27% more livestock than loan-ineligible households. Furthermore, there is no difference in mental health and food insecurity between the two groups in these low-flooded villages. These effects remain persistent one year after the floods. Taken together, these results provide evidence that credit generates positive and consistent returns in the absence of a shock. However, when households are hit by a shock, these returns disappear, and their resilience actually decline. This provides some of the first well-identified evidence of the proposition that currently indebted households actually face greater climate vulnerability.

My paper contributes to several branches of literature. First, I contribute to the literature examining the impact of microcredit. There is an extensive body of work focusing mostly on its effects on productivity and growth. The consensus in this literature is that the impact of microcredit is, at best, modest and not transformative as envisioned by its initial proponents (Attanasio et al., 2015; Crépon et al., 2015; Banco, 2014; Augsburg et al., 2015; Banerjee et al., 2015a; Tarozzi et al., 2015). I contribute to this literature in three ways. First, most existing studies focus on the impact of microcredit on marginal borrowers (Banerjee et al., 2015b; Wydick, 2016; Morduch, 2020). These studies expanded microcredit to communities where formal financing was already available. In my study, I evaluate the impact of microcredit on infra-marginal borrowers by examining the expansion of microcredit to a population with no access to formal financing prior to the study. Given that microcredit could have heterogeneous effects (Meager, 2019; Banerjee et al., 2019), it is important to identify populations that can derive the maximum benefit. Infra-marginal borrowers could be one such population, as they are early adopters and the primary target of lenders before lenders begin experimenting at the margins. Second, most credit papers have looked at the average effect of credit. In my study, I not only analyze the average effects, but because I also consider variation in exposure to an important shock, I can uniquely assess credit's ability to build household resilience to shocks. Third, there are fewer studies examining the impact of microcredit on vulnerable communities partly because financial institutions are less likely to lend to these communities due to the fear of default (Amin et al., 2003; Kikstra et al., 2022).

Second, this paper contributes to the literature examining how to improve households' resilience to climate change. This literature has so far looked at the impact of introducing risk-reducing technologies (Emerick et al., 2016; Jones et al., 2022), infrastructure improvements (Brooks and Donovan, 2020) and information (Leeffers, 2023). A few papers within this literature have considered the role of financial products like grants and credit.[5] Most closely relevant to this study are two papers that have looked at the impact of microcredit on dealing with natural shocks. Lane (2022) finds that offering guaranteed credit to agricultural households facing flood risk, increases welfare through two channels: an ex-ante insurance effect, where people increase investment in riskier but profitable technologies, and an ex-post effect, where people use loans to smooth consumption. Demaont (2014) finds that being a member of a Self-Help Group increased access to credit for the members, which resulted in higher food security following a drought. I contribute to this literature by studying the effects of providing access to credit *before* a shock on household growth and resilience. While it is clear that access to credit lines aids recovery after shocks, the impact of access to credit prior to a shock on household investment and resilience remains unclear. Access to loans before a shock may create complex interactions between growth and resilience that may not occur when credit is provided solely for recovery.

The paper proceeds as follows: In Section 2, I discuss the program, the context, and the loan product. Section 3 describes the 2022 floods in Pakistan. Section 4 describes the data and the outcome measures. Section 5 describes my empirical approach, and Section 6 presents the results. Section 7 concludes.

[5] Most of the papers have looked at the impact of cash transfers on resilience, for example Premand and Stoeffler (2020), Pople et al. (2021), Macours et al. (2012), and Asfaw et al. (2017)

2 SUCCESS program

The Sindh Union Council and Community Economic Strengthening Support Programme (SUCCESS) is Pakistan's largest women-led multi-stakeholder development project, launched in 2016. The main goal of the program is to support the provincial government in developing a local development policy emphasizing community-driven development.[6] The program is based on the rationale that growth can be achieved by organizing women into community institutions and building their skills and capital.

The program is implemented in the Sindh province of Pakistan. Sindh is the second most populous province in Pakistan with a population of 48 million. The program is implemented in 8 of the 24 districts in Sindh. These districts include Tando Muhammad Khan, Sujawal, Matiari, Tando Allahyar, Larkana, Kambar Shahdadkot, Dadu, and Jamshoro. Similar programs have been implemented in other districts of the province by the Government of Sindh (GoS).[7] Table A1 shows a comparison of the districts where the program is implemented with the remaining districts of the province. Overall, the districts where the program is implemented appear to be slightly poorer, with fewer households owning land and livestock.

SUCCESS program has two main components. The first is the social mobilization of women in the communities, which is achieved by creating women-only community organizations that are run by the women in the community. Three-tiered community organizations are formed (Figure A1). The basic form of these local organizations is at the neighborhood level and is called Community Organizations (COs). All households living in that neighborhood are eligible for membership in the CO. COs subsequently federate into Village Organizations (VOs). VOs are formed by considering the geographical proximity and access between different settlements, where women can easily attend monthly VO meetings. Village organizations subsequently federate into union council-level Local Support Organizations (LSOs). Each VO nominates up to two of its members to represent the VO in the LSO. So far, the program has mobilized around 607,943 women into 30,274 COs, 3,460 VOs, and 314 LSOs (Fazal Ali Saadi, 2022).

The second component of the program offers subprograms, including loans, grants, micro-health insurance, and skills training. These subprograms are available only to women who are members of the COs. Moreover, among the members, not everyone is eligible for these subprograms. Eligibility is determined through poverty score cutoffs. Households with a poverty score between 0 and 9 receive one-time grants, while interest-free loans are provided to those with scores between 10 and 23. Micro-health insurance is available to households

[6] https://rspn.org/success/tag/success/

[7] A similar program is currently being run by the GoS in 6 other districts of Sindh, as discussed at https://www.pprp.net.pk/about.html

with scores between 0 and 12, and skills training is offered to those with scores between 0 and 23.[8] As a result of the program, over 50,000 households have received grants, 100,000 have received loans, 137,000 have received micro-health insurance, and 27,000 have received skills training. Further details about these components are provided in the Appendix E.

2.1 Setting & Context

The province of Sindh is extremely vulnerable to natural shocks.[9] The occurrence of floods is common in the province, with massive flooding episodes in 2003, 2004, 2005, 2010, 2011, 2012, 2013, 2015, and 2022. Most of these floods are caused by rainfall during the monsoon season. In a risk assessment survey conducted by the World Bank, it was found that around 60% of the union councils in the Matiari district, where I conducted my outcome survey, are at flood risk (Sindh, 2022). In the surveys, 35% of the sampled households mentioned that flooding was common in their area, and 30% mentioned that they are afraid floods would occur again in the next two years. Considering the flood risk, people do take some precautionary measures, such as house repairs, to safeguard their homes from floods. These actions, however, are not enough. People do not have access to flood insurance, and there is no flood warning system. People mostly have to rely on their own resources with limited support from the government.

Rural Sindh is also one of the poorest regions in Pakistan with around 75% of the population living below the poverty line (UNIDO, 2021). Most of them work as daily wage laborers in the village, where they work in the fields owned by landlords. A small number of households own a business (1%) or are involved in agriculture (3%). People are credit constrained and have limited access to formal and informal credit. 1% of the households have ever taken a loan from a bank or an NGO. A higher, but very limited, share (10%) have taken an informal loan either from family/friends or shopkeepers.

Housing is the most common asset people possess. In the Matiari district, 91% of the households mentioned that they own their house and have been living in the same house for more than 40 years. The majority of the houses have only one room for six people with no toilet. There is, however, substantial variation in housing quality, as 23% of the houses have a concrete floor and 52% have a concrete ceiling. People spend around 4% to 5% of their monthly household income on their housing. Many people want to invest more on their

[8] Although skills training shares the same cutoff score as loans, less than 6% of eligible households have received it. I also show that my results remain robust when excluding households that received skills training.

[9] The topography of Sindh Province is almost flat and located at the bottom of the Indus basin. The surplus water of the Indus River and its tributaries, including monsoon rains, has to pass through Sindh. In the case of a breach, the outflowing water cannot be drained back into the river at any point (https://pdma.gos.pk/rain-flood/)

housing. When asked hypothetically what they would do if they get a loan of 15,000 PKR or 150,000 PKR, 25% and 50% of the respondents mentioned that they will use it on their house.

The second asset people have is livestock. 44% of the households have some form of livestock. Half of the people who have livestock own the livestock while the rest have livestock on a sharing basis. In this arrangement, one household buys the livestock and gives it to the other person for rearing. The rearing household is responsible for arranging fodder and can consume the milk. Any profit from selling the shared livestock, or offspring of the shared livestock is evenly divided. The most common form of livestock people have is goats, followed by buffaloes.

Livestock plays a crucial role in income generation for many households. Families often sell milk and male offspring in the market to earn a livelihood. Livestock purchased on a shared basis is primarily intended for future sale. Households buy young animals, raise them for a couple of years, and sell them when they grow. Many families prefer to wait for the Eid-ul-Adha festival to sell their livestock, as the demand for livestock significantly increases during this period, allowing them to secure better prices.[10]

2.2 Loan product

Eligible COs formed under the SUCCESS program are given a capital grant. These COs are asked to use the capital grant as a revolving fund to provide loans to the poorest women in the village. The organizations are responsible for managing these loans, which include, among other things, ensuring that only eligible members receive loans, disbursing the loans to the beneficiaries, and collecting monthly repayments.

To be eligible for a loan, a household should have a woman who is a member of the CO. The household should also have a poverty score between 10 and 23 at the start of the program. Figure 3 confirms that the NGO has adhered to this rule in the allocation of loans. Once the loans are approved, the CO president collects the loan amount from the bank and gives it to the female member of the beneficiary households in cash.

The loans given in the SUCCESS program are individual-liability loans with monthly repayments and no grace period. The loans are interest-free; however, there is a one-time service fee of 3% that households need to pay. The loans are uncollateralized and have a tenure of 12 months.[11] The maximum amount that can be given is 14,000 PKR ($50). Each

[10] During Eid-ul-Adha, Muslims around the world, including in Pakistan, observe the tradition of sacrifice by slaughtering a cow, goat, or other livestock.

[11] There are some loans (<2%) where there are no monthly repayments. These clients are required to make a lump sum payment at the end of the year

eligible member can take a total of 5 loans, with each subsequent loan being higher in amount by 10%.

The primary goal of the loans is to support poor households in starting income-generating activities. Beneficiaries are responsible for identifying their own needs and deciding how to best use the loan. As part of the process, each beneficiary submits a Micro Investment Plan (MIP) outlining the intended use of the loans before approval. However, neither the NGO nor the COs enforces the MIP, leaving beneficiaries free to use the funds as they saw fit.[12]

To ensure timely repayments, the COs guarantee the prompt repayment of loans by their beneficiary members. Additionally, two other CO members are required to personally guarantee the loan recipient's timely repayment. Furthermore, any member wishing to apply for a new loan has to fully repay any outstanding loans first. Following the floods, the COs suspended the issuance of new loans to both new and existing beneficiaries. A six-month moratorium was granted to households affected by the floods.

3 Floods - 2022

In the summer of 2022, Pakistan experienced one of the world's deadliest floods. During the monsoon months, the country was hit by intense rainfall that far exceeded normal levels, leading to a catastrophic flood. A state of emergency was declared as one-third of the country was submerged. It is estimated that around 8 to 9 million people are at risk of being pushed below the poverty line due to the floods. The direct impact on GDP is projected to be around 4.8% of FY22 GDP (Initiatives, 2022).

Figure 1 shows the extent of the floodwaters. Most of the floodwaters were concentrated in the province of Sindh, where this study is conducted. Sindh was most severely impacted by the floods. While the country received 350% more rainfall than the average over the past 22 years, rural Sindh experienced 725% more rainfall. 23 of the 29 districts in the province were categorized by the government as calamity-hit areas, and 70% of the overall damages and losses were incurred in Sindh (Division, 2023). It is estimated that the province will require $7.9 billion for post-flood recovery and reconstruction (Bank, 2022). In response to the floods, the government of Sindh, in collaboration with the World Bank, launched the Sindh Flood Emergency Rehabilitation Project ($510 million) to rehabilitate damaged infrastructure and provide livelihood opportunities to the affected residents (Bank, 2022).

Pakistan is highly vulnerable to floods, with over 32% of the population exposed to high flood risk (Rentschler and Salhab, 2020). Although the 2022 floods were the most devas-

[12] In the surveys we conducted, beneficiaries reported various ways they used the loan, with a significant portion being allocated towards consumption.

tating in the country's history, Pakistan has faced other severe flooding events. In 2010, floods submerged one-fifth of the country, affecting more than 20 million people. Since 1970, Pakistan has experienced more than 100 floods.[13] Figure A2 shows the share of the population impacted by floods since 1970. With climate change, there are concerns that such extreme flooding events will become more common in Pakistan (World Bank Group, 2021) and globally (Hirabayashi et al., 2013).

4 Data

4.1 Poverty Assessment Survey

The poverty assessment survey is a census survey conducted by the NGO in 2016 before any loans. The survey covers the rural areas of all eight districts where the program is implemented. The main purpose of the poverty assessment survey is to construct the poverty scorecard (PSC) for each household, which is later used to determine loan eligibility. In my analysis, I use the poverty assessment survey data to test for the validity of the RD. The survey collected information on two dimensions: household demographic data and household assets. Table 1 shows the summary statistics from the poverty assessment survey for the four districts where the program is implemented.[14]

4.2 Program Intervention data

Program intervention data identifies household members who joined the CO and received a subprogram, along with the type of the subprogram. Program intervention data is maintained regularly by the NGO. I have access to the program intervention data from 2018-2023. The program intervention data on loans includes the number of loans taken, date when loan was taken, loan tenure. Moreover, I also have the monthly repayment data for each loan. I am using the administrative data to understand the share and characteristics of the population who joined these COs and received these subprograms. I use the loan repayment data to understand repayment behavior of the beneficiaries.

4.3 Data on flood intensity

For rainfall, I use the Climate Hazards Group Infrared Precipitation with Station data (CHIRPS) dataset, developed by the Climate Hazards Center at the University of California,

[13] https://www.emdat.be/

[14] Of the eight districts, I only have access to data for the four districts where the activity was implemented by NRSP, the NGO who I partnered with.

Santa Barbara. CHIRPS is a 35+ year quasi-global dataset that contains daily rainfall data at a resolution of 0.05.[15] I use the household geo-coordinates to construct the median geo-coordinate for each village and collect the daily rainfall for each household from 2008 to 2024 for the monsoon months (June to September).

I use the rainfall data to assess how household resilience and welfare change with flood intensity. Since these floods were caused by rain, the difference between the rainfall villages received in 2022 and the mean rainfall they received from 2008 to 2021 is used to categorize villages into high- and low-flooded groups. To increase statistical power, instead of using a continuous measure of flood intensity, a binary measure is used. Villages where the difference is above the median are classified as high-flooded villages. Rainfall data is chosen over floodwater extent as it is more exogenous; floods depend on terrain, which could influence other outcomes. Table A2 shows that the rainfall measures correspond with the floodwater extent reported by households in our surveys.

4.4 Outcome data

I conducted two rounds of surveys to collect outcome data. The first round of surveys was conducted right after the 2022 floods. The surveys were conducted in November 2022 and were administered in person by the enumerators. The sample included 3500 households from 98 villages in one district of Sindh, where the program was implemented.[16] Below, I describe the sampling strategy and the outcome measures.

I restricted our sampling frame to only those COs where at least one member had received a loan. Figure A3 shows the distribution of the COs with the share of loan-eligible members, and the share of all members who had taken a loan. As I had the poverty score of all the households in the poverty assessment survey, I restricted the sampling frame to all the households in the villages with a poverty score between +/-4 points of the cutoffs for loans to increase power. I selected +/- 4 using data-driven bandwidth selection as suggested by Calonico et al.(2020). I had the replacement list of households, in case if some households could not be identified due to a limited set of identifiers.

After a year of the floods, I conducted a followup survey. There were two main reasons that motivated the followup survey. First, I wanted to observe how resilience and welfare metrics changed over time in the high- and low-flooded villages—that is, whether the gap between these villages was widening or narrowing over time. Second, and relatedly, I wanted

[15] CHIRPS builds on previous approaches to 'smart' interpolation techniques and high-resolution, long-period precipitation estimates based on infrared Cold Cloud Duration (CCD) observations (Funk et al., 2015).

[16] Due to budgetary constraints, I had to limit data collection to only one district.

to know whether households sell their livestock to finance house repairs or other needs. I surveyed the household right after the Eid-ul-Adha festival when there is a high demand for livestock. If households wanted to sell their livestock, this would have been the best time. In the follow-up survey, I attempted to resurvey all the households that I surveyed earlier. The following figure provides a timeline of the different project activities.

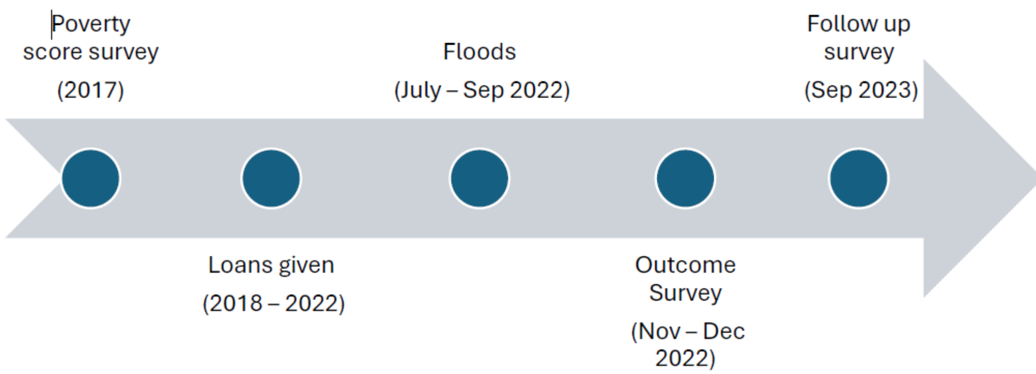


Figure: Timeline of Major Activities

4.4.1 Attrition

Attrition from the survey sample is one of the concerns in the follow-up surveys conducted nearly 5 to 6 years after the initial census (poverty assessment survey) by the NGO. Attrition in our setting can occur for two reasons. First, failure to identify the sampled households in the field. From the census, we had the names of the household head and household members. We also had the geo-coordinates for the households. These geo-coordinates were useful in identifying the village of the household but not the exact location of the house. Once we were in the villages, we relied on the household head and member names to identify the household.

Second, the floods in 2022 resulted in massive displacements with people temporarily relocating to safer places. Although we conducted our survey around four months after the floods ended, there was still a chance that people might not have returned to their homes. Attrition in the survey itself is not a major concern, but differential attrition across the discontinuity within villages could lead to biased estimates.

Table 2 reports the attrition rates. Panel A presents the attrition in the outcome survey conducted right after the floods in 2022. There is an attrition rate of 7%. The probability of differential attrition across the discontinuity is very small and is not significant. There is no differential attrition between the high- and low-flooded villages. Panel B presents the attrition rates in the follow-up survey conducted after a year. In the follow-up survey, attrition increased to 13%. Most of the attrition comes from the flooded villages (19%) and from one union council where we encountered logistical issues (Table A3). Excluding that union council, the attrition rate is 5%. Table A4 shows that those who attrited are poorer, with a lower poverty score and fewer non-livestock assets. A larger fraction of attrited people have house damaged by floods. Importantly for our analysis, there is no differential attrition across the discontinuity within the high- and low-flooded villages.

4.5 Outcome measures

I focused on three sets of outcomes. The first set of outcomes relates to household investments. This includes detailed information on household investment in business, agriculture, livestock, non-livestock assets and house quality. For non-livestock assets I collected data on different types of assets household own and constructed an index using Anderson (2008). Likewise, I constructed an index on housing quality using different household metrics. In the survey, I recorded many features about the house including the material of the roof, material of the floor, number of rooms, and type of toilet. I also collected detailed data on the migration history of individual household members.

The second set of outcomes focuses on flood-related damages, including relocation and the extent of losses incurred. In our survey, I asked respondents if they relocated during the floods. For those who did, I collected additional details on their relocation destination, the number of days they stayed, and total expenses incurred. To assess flood damages, I recorded whether the household experienced losses in livestock or sustained any damage to their home, along with the specific type of damage.

Our third set of outcomes relates to household resilience. I asked multiple questions regarding food security and used them to construct an index based on Anderson (2008). These questions included asking households if any household member had to reduce meal portions, borrow food, wish they had more food, experience insufficient food, go a day without a meal, or miss eating two meals. To create an index on mental health, I asked respondents about the frequency of feeling lost, crying, not wanting to work, and experiencing restless sleep in the week before the survey. Additionally, I asked households if they took any measures to repair the damages to their house or other assets.

5 Empirical strategy

Our empirical design relies on the fact that eligibility for loans is determined based on the household poverty score. Assuming that the poverty score is not manipulated, I can use a regression discontinuity design to identify the impact of loans by comparing people who are eligible for loans and are right at the cutoff to people who barely missed the eligibility for loans due to having a slightly higher poverty score. Under certain conditions, households that narrowly missed being eligible for a loan are a reasonable counterfactual to those barely eligible for a loan. Our main estimation equation will be the following:

$$Y_{iv} = \alpha + \gamma \mathbf{1}_{\{PSC_{iv} \leq 0\}} + \beta_1 PSC_{iv} + \beta_2 PSC_{iv} * \mathbf{1}_{\{PSC_{iv} \leq 0\}} + \mu_v + \epsilon_{iv} \tag{1}$$

Here Y_{ivt} is the outcome of interest for a household i in village v at time t. PSC_{iv} is the difference between the poverty score of the household i and the cutoff score for being eligible for a loan ([-4, 4]). ($PSC_{iv} \leq 0$) takes a value of 1 if the household is eligible for a loan and 0 if the household is ineligible for a loan. μ_v are the village fixed effects and ϵ_{ivt} is the error term. The γ provides an estimate of the Intention to Treat (ITT) for observations around the cutoff. Observations are weighted with a triangular kernel. Standard errors are clustered at the village level.

To study the differential impact after the floods in the high- and low-flooded villages, I employ a difference-in-discontinuities (diff-in-disc) design, similar to Grembi et al. (2016). In the diff-in-disc design, I combine two sources of variation: loan eligibility (eligible vs. ineligible) and flood severity (high vs. low). I examine the difference between high- and low-flooded villages by analyzing the discontinuity at the poverty score cutoff of 23, which determines loan eligibility. Our estimation equation will be the following:

$$\begin{aligned} Y_{iv} = \alpha &+ \gamma \mathbf{1}_{\{(PSC_{iv} \leq 0)\}} + \beta_1 PSC_{iv} + \beta_2 PSC_{iv} * \mathbf{1}_{\{(PSC_{iv} \leq 0)\}} \\ &+ \beta_3 \mathbf{1}_{\{HighFlooded_v\}} + \beta_4 PSC_{iv} * \mathbf{1}_{\{HighFlooded_v\}} \\ &+ \delta \mathbf{1}_{\{(PSC_{iv} \leq 0)\}} * \mathbf{1}_{\{HighFlooded_v\}} + \beta_5 \mathbf{1}_{\{(PSC_{iv} \leq 0)\}} * \mathbf{1}_{\{HighFlooded_v\}} * PSC_{iv} \\ &+ \mu_{UC} + \epsilon_{iv} \end{aligned} \tag{2}$$

Here, $HighFlooded_v$ is a dummy variable that equals 1 if the village v is a high-flooded village and 0 otherwise. The coefficient γ provides the ITT effect in the low-flooded villages. The $\gamma + \delta$ provides the ITT effect in the high-flooded villages. The parameter δ provides the difference-in-discontinuities estimator and identifies the difference in ITT effects between the high- and low-flooded villages. μ_{UC} are the union council fixed effects.[17] Observations are weighted with a triangular kernel. Standard errors are clustered at the union council level.

I test the robustness of my main results using a local randomization approach. Evidence suggests that when the running variable is discrete, the continuity-based RD design can be problematic, as the standard smoothness assumption may not hold. This can lead to issues in interpreting coefficients or conducting inference (Kolesár and Rothe, 2018). To address this issue, one suggested approach is to use a local randomization method, where scores are assumed to be as if randomly assigned within a small window near the cutoff. This approach allows for treatment assignment to be considered as if experimental (Cattaneo et al., 2019).

5.1 Validity of the RDD

The validity of the RDD design in our setting relies on two assumptions. The first assumption requires that households do not behave strategically around the cutoff. The second assumption is that the relevant factors that could affect the outcome are smooth around the cutoff. Conventionally, the first assumption can be tested by performing a manipulation test of the running variable under the null hypothesis that the distribution of the poverty score is smooth around the cutoff. However, the conventional tests used to check for manipulation only work for cases when the running variable is continuous. These tests are less reliable when the running variable is discrete (Frandsen, 2017).

A visual examination of the poverty score suggests that the distribution of the poverty score has big jumps (Figure 2). However, the jumps are not the result of manipulation but are due to the formula used to construct the poverty score. The poverty score is a discrete number with values from 0 to 100. The higher the poverty score, richer is the household. Poverty score is constructed using the weighted sum of 12 indicators. These indicators include the number of people in the household below the age of 18 and above the age of 65, the education level of the household head, children between the ages of 5 and 16 attending school, number of rooms per person in the house, toilet type, the type of assets the household possesses, livestock, and agricultural land. The weights were determined by the NGO in 2015 before the implementation of the program. Appendix D provides the weights given to each of these 12 indicators.

In Figure 4, I show the distribution of the poverty score constructed using the government-collected data for the same district in the same year when the NGO conducted the poverty assessment survey to construct the poverty score. If the jumps in the poverty score are due to households manipulating their poverty score, there should not be similar jumps in the

[17] A union council is an administrative unit consisting of multiple villages. On average, a union council has 10-12 villages.

poverty score constructed using government collected data where households do not have an incentive to manipulate precisely at the cutoff.

Next, for households eligible for loans and right at the cutoff, I look at the probability of getting a certain value for each of the indicators used to construct the poverty score. Each indicator used to construct poverty score can take multiple values depending on the household response. If households closer to the cutoff who are eligible for a loan are more likely to take certain values for some indicators, it could suggest manipulation. If there is no such pattern then there is less chances of manipulation. To do that I run a regression of a being eligible for a loan on the each unique value of each indicator.[18] I restrict the sample to households with poverty score between 22 and 25. Figure 5 reports the beta coefficients from these regressions. Households eligible for loans are likely to get lower values for all 12 indicators suggesting that there are less chances of manipulation.[19]

The second assumption in our design is that variables that could affect the outcome should be continuous around the cutoff. To test this, I examine the continuity of various demographic and non-demographic variables at the cutoff. I start by showing no discontinuity in the 12 indicators used to construct the poverty score. I show the continuity for all the households in the district and the households in our sample. As shown in Figure 6, I do not find any evidence of discontinuity in these variables.

Using the baseline survey collected by the NGO from a larger sample, I also check for continuity in other variables such as annual earnings, farm income, non-farm income, savings, borrowing, and lending. I do this for the districts the NGO collected data in the baseline and also for the district where I conducted the endline survey. The latter reduces our sample size. In both checks, I do not find any discontinuity, as shown in Figure 7.

5.2 Balance between high and low flooded

Table 3 reports whether high- and low-flooded villages are similar on observable characteristics before the floods. In panel A, I report the balance on all the variables that are used to construct the poverty score. In panel B, I report balance on characteristics specific to the program intervention. Of the 12 indicator variables used to construct the poverty score, only children's schooling is significantly different between high- and low-flooded villages. There is also no difference in the average poverty score or the population of the villages. In terms

[18]

$$Indicatorvalue_{iv} = \alpha + \beta * \mathbf{1}_{\{(PSC_{iv}<0)\}} + \mu_v + \epsilon_{ivt}$$

[19] In the outcome survey, I also asked households if they knew their poverty score and the cutoff scores for getting a loan. Only 5% of households reported knowing these cutoffs, and among them, only 3% provided correct responses.

of the membership of the COs or uptake of the different components of the program, I do not see any differences. Likewise, there is no difference in the share of households eligible for loans, loan take-up and loan repayment rates.

6 Results

6.1 Loan takeup & Repayments

Table 4 shows the program's impact on access to borrowing. Column 1 indicates that households with a poverty score between 10 and 23, which are eligible for the SUCCESS loan, are 46% more likely to take a loan. Column 2 shows that the average loan amount among these eligible households is 5,744 PKR ($20). The loan take-up in this setting is higher compared to other studies, which have found a modest demand for microcredit, ranging from 17% to 31% (Banerjee et al., 2015b). The higher take-up rate in this context may be attributed to lending to inframarginal borrowers or the low interest rates charged.

Table 4 also reports the impact of loan access on other forms of borrowing. Almost no one, whether eligible or ineligible, borrows from formal banks or microfinance institutions (column 3). This is unsurprising, as no formal financial institutions offer loans to these communities due to concerns about high default risk and the lack of collateral. In this setting, borrowing from family, friends, and shopkeepers is more common. There is no evidence that the program has reduced borrowing from these sources. The point estimate for informal lending is -0.5 percentage points (column 4), and for shopkeeper loans, it is -0.2 percentage points (column 5), but neither is statistically significant. These results suggest that households are, in fact, credit constrained and they do not use the cheaper loans to substitute for other forms of borrowing.

The last column of Table 4 provides some insights into late repayment and default behavior. I calculate the late repayments and default behaviour using the administrative data from the NGO. Default behaviour is measured by the ratio of the outstanding principal to the loan amount.[20] On average, about 2% of the loan principal is past the due date, a figure comparable to that of other microfinance institutions in the country.

6.2 Impact of credit before floods

I first look at the impact of credit on the type of ex-ante household investment. Given that households have multiple investment options with varying levels of risk, I consider a range of

[20] I restrict the sample to loans with a due date before August 2022

investments. These include running a business, agriculture, livestock, migration, and non-livestock assets. Table 5 reports the impact of access to credit on these investments. The associated RD graphs are shown in Figure 8

Access to credit led to an increase in livestock at both the intensive and at the extensive margins. Households eligible for a loan are 6 percentage points more likely to own livestock (column 4). Similarly, access to credit results in an increase in herd size by 0.34 (column 5), corresponding to a 22% relative increase in the number of livestock compared to loan-ineligible households. A closer inspection of the data reveals that this increase is primarily due to a rise in the number of goats (Table A5). Interestingly, the increase in livestock is entirely driven by an increase in owned livestock, with no change in shared livestock.

Column 6 of Table 5 reports a negative effect of credit on household assets. Being eligible for loans reduces assets by 0.068 standard deviations. Similarly, credit decreases investment in housing quality by 0.106 standard deviations (Column 7). In terms of individual components, there is a significant negative impact on the probability of having a concrete roof (-4.9 percentage points), a concrete floor (-4.6 percentage points), the number of rooms (-0.06), and having a toilet (-5.3 percentage points) (Table A6). These results suggest that households might be diverting expenses from assets and housing to finance livestock. This is plausible for two reasons. First, livestock is lumpy. The loan amount was insufficient to purchase a goat, which typically costs around 20,000 to 30,000 PKR, or 42% to 114% more than the average loan amount of 14,000 PKR provided under the program (Ahmed et al., 2022). Additionally, there is a fixed cost associated with setting up a goat shed. As a result, households need to supplement the loan to afford livestock. Furthermore, the monthly cost of rearing livestock is 10% of the household's monthly income. Since livestock in this context does not generate monthly income, households need to reduce other expenses to cover these recurring costs. Second, evidence suggests that households prefer to allocate their resources toward investments with higher perceived returns (Banerjee et al., 2015a). In this setting, households believe that returns from livestock exceed those from investing in assets and housing.

There is no impact of access to credit on starting a business, engaging in agriculture, or migrating. The point estimates are close to zero and not statistically significant (Columns 1-3 in Table 5). Based on the 95% confidence interval, we can reject effects larger than 1.5 percentage points. The lack of effect on these outcomes is not due to the loan amounts being insufficient to finance them. Instead, households invested in livestock for two reasons. First, they have some experience with rearing livestock; at baseline, 44% of households own livestock. Second, anecdotal evidence suggests that households perceive returns from livestock to be higher than returns from other types of investment.

6.3 Impact of floods in the absence of credit

Before discussing the post-flood outcomes based on loan eligibility, I first examine the impact of the floods. To do this, I compare loan-ineligible households in high- and low-flooded villages. Since loan-ineligible households in these villages have similar characteristics prior to the floods (as shown in Table 6), any observed differences can be attributed to the floods. Loan-eligible households are excluded from this comparison to avoid conflating the effects of loans with the impact of the floods.

To assess the impact of the floods, I examine two aspects: the share of households that relocate during the floods and the extent of flood-related damage. The floods result in a higher rate of household relocation. Column 1 of Table 6 shows that 28% of households in low-flooded villages relocate temporarily, compared to a higher, though statistically insignificant, relocation rate in high-flooded villages (8.6 percentage points).

The floods also cause significant livestock losses. In low-flooded villages, 17% of households lose livestock, while households in high-flooded villages are 10 percentage points more likely to experience livestock loss (column 2). In terms of the number of livestock lost, households in low-flooded villages lose 0.25 of their herd on average, compared to 0.67 in high-flooded villages (column 3). Additionally, the floods cause damage to houses, with 65% of households in low-flooded villages reporting damage. This share is 6 percentage points higher in high-flooded villages, although the difference is not statistically significant (column 4)

6.4 Overall impact of credit on post-flood outcomes

Next, I look at the impact of these ex-ante investments on household ex-post resilience and welfare after the floods. I begin by reporting the results from the first outcome survey, conducted immediately after the floods, followed by the results from the follow-up survey conducted a year later.

Damages & Relocation during floods I examine two types of damages: livestock losses and damage to housing. Table 7 presents these damages along with relocation status, while the corresponding RD figures are shown in Figure 9. About 22% of households in the loan-ineligible households lose livestock during the floods. The probability is 1.6 percentage points higher for loan-eligible households, but this difference is statistically insignificant. On the extensive margin, loan-ineligible households lose an average of 0.46 livestock, representing around 30% of their herd. In contrast, loan-eligible households lose 0.745 livestock, or approximately 42% of their herd—60% more than the ineligible households. These higher losses among loan-eligible households may be partly explained by herd size. Figure A4 shows that the mortality rate is higher for households with larger herds, which likely contributes to the greater losses experienced by eligible households. Additionally, households eligible for loans experience greater damage to their homes. Column 4 indicates that eligible households are 3.4 percentage points more likely to have their houses damaged compared to ineligible households. However, there is no significant difference in the intensity of the damage.

Loan-eligible households are also more likely to temporarily relocate during the floods. Compared to loan-ineligible households, loan-eligible households are 5 percentage points more likely to relocate during floods(Column 1). However, I find no effect on the intensive margin, such as the number of days stayed, the place they stayed, or the expenses incurred during relocation. The increased relocation among loan-eligible households could be due to several factors. One possibility is that they are more likely to experience housing damage, making relocation necessary. Another reason could be that loan-eligible households are better able to arrange funds for relocation, as households that relocated spent 50% of their monthly household income on relocation expenses. Anecdotal evidence supports both of these possibilities.

Resilience I look at multiple metrics of ex-post resilience and welfare. These metrics include: livestock, food insecurity, mental health, assets, and repairs. Table 8 reports the impact of access to credit on these metrics, with the corresponding RD figures shown in Figure 10.

Loan-eligible households are still more likely to own livestock after the floods. Compared to loan-ineligible households, they are 5.8 percentage points more likely to own livestock (Column 1). However, the effect on the extensive margin has gone down and is not statistically different from zero. The estimate has a magnitude of 0.08, which translates into 7 percentage points more than the loan-ineligible households (column 2). The difference between the two groups before the floods is 22 percentage points. Column 3 reports that loan-ineligible households have 0.069 standard deviations fewer assets than loan-ineligible households. The magnitude of the estimate is similar to the ex-ante estimate.

Columns 4 - 6 in Table 8 show no significant differences between the two groups in terms of food insecurity, mental health, and home repairs. The estimate for food insecurity is -0.004 standard deviations and is not statistically significant. The estimate on the mental health index is -0.089 standard deviations, suggesting a potential decline in the mental health of loan-eligible households ex-post. However, this estimate is not statistically different from zero. The 95% confidence interval ranges from -0.22 to 0.044 standard deviations, ruling out effects larger than 0.044 standard deviations. Similarly, loan-eligible households are 3.7 percentage points less likely to make repairs to their homes ex-post, but this estimate is also not statistically significant. The 95% confidence interval ranges from -8 percentage points to 1 percentage point, effectively ruling out effects larger than 1 percentage point.

6.4.1 Heterogeneity of ex-post outcomes by flood intensity

I next examine the ex-post outcomes by flood intensity using estimation equation 2, where I combine variation in loan eligibility with flood intensity and analyze the difference in discontinuities between high- and low-flooded villages. I first report the results from the survey conducted right after the floods, before discussing the outcomes a year later.

Column 1 in Table 9 shows that the higher probability of having a damaged house after the flood is driven by households in high-flooded villages. The first row of Column 1 indicates that in low-flooded villages, the probability of having a damaged house is 2.6 percentage points, which is not statistically significant. The coefficient on the interaction term, which captures the difference in discontinuities between high- and low-flooded villages, is 3.2 percentage points. This suggests a differential probability of house damage between the two types of villages. Although the interaction term is not statistically significant, the total effect on house damages in high-flooded villages (5.8 percentage points) is significant, with a p-value of 0.05.

Likewise, the drop in livestock is primarily driven by households in high-flooded villages. Ex-post, loan-eligible households in the low-flooded villages still have more livestock. They are 9.4 percentage points more likely to own livestock and have 0.36 more livestock. Both these estimates are significant at the conventional levels. In contrast, for loan-eligible households in high-flooded villages, livestock has decreased. The interaction term shows a 7 percentage point decrease in the probability of owning livestock and a 0.468 decrease in the number of livestock, with only the latter being statistically significant. Overall, loan-eligible households in high-flooded villages are 2 percentage points more likely to own livestock and have 0.09 fewer livestock compared to loan-ineligible households in these villages, but neither of these estimates is statistically significant.

Column 7 shows a decline in mental health in high-flooded villages. In low-flooded villages, the estimate on mental health is -0.06 standard deviations and is not statistically significant. However, in high-flooded villages, the estimate is -0.18 standard deviations and statistically significant. There are no differential effects by flood intensity on relocation, assets, food insecurity, or repairs, as the estimates for the interaction terms across these outcomes are close to zero and not statistically significant.

Table 11 reports the differential results for high- and low-flooded villages from the follow-up survey conducted a year after the floods. Loan-eligible households in low-flooded villages are still more likely to own livestock. Row 1 in Columns 1 and 2 shows that loan-eligible households in low-flooded villages are 9.6 percentage points more likely to own livestock and have 0.24 more livestock. In contrast, loan-eligible households in high-flooded villages were less likely to own livestock. The interaction term on the probability of owning livestock has a magnitude of -12.5 percentage points, meaning that loan-eligible households in high-flooded villages are 3 percentage points less likely to own livestock. Additionally, the interaction term on the number of livestock (Column 2) is -0.50, indicating that loan-eligible households in high-flooded villages have 0.26 fewer livestock—20% less than loan-ineligible households.

Column 3 shows that the results on mental health and food insecurity in the followup are almost exactly similar to right after the floods. There are still no differential effect on food insecurity by flood intensity. Loan eligible household in the high-flooded villages still have worsening mental health and there is no change in the magnitude compared to the right after the floods estimate. In terms of the loan repayment, compared to the low-flooded villages, high-flooded villages had 4 percentage points more principal that is past due (Figure 12).

6.5 Robustness

I test the robustness of my main results using a local randomization approach, restricting the window to +/-1 points from the cutoff. My main ex-ante result—that access to loans increases livestock and reduces non-livestock assets and housing quality—is robust when using this local randomization approach (Figure A5). Similarly, the findings that ex-ante investment leads to higher growth in low-flooded villages and reduces welfare and resilience in high-flooded villages after the floods are also robust to local randomization approach (Figures A6 to A7).

Figure A5 to A7 also show that my main results are robust to excluding households that have received a skills training. Skills training have the same cutoff as loans, but only 6% of the eligible households have received skills training (Figure A8).

7 Conclusion

Access to credit is widely regarded as one of the most important drivers of growth and development. In countries with credit market frictions, improving access to credit can create opportunities for profitable investments. As climate change intensifies, there is growing momentum for expanding access to credit. In a world facing increasing flood frequency and a higher share of the poorer population exposed to floods, it is essential to understand how credit can impact household resilience. In this paper, I examine the relationship between growth and resilience, leveraging Pakistan's largest women-led development program, which provides loans to ultra-poor, landless households

The SUCCESS program improves access to credit. Among loan-eligible households, those with a loan increase from 1% to 46%. The improved access to loans leads to an increase in livestock, a high-risk asset with a mortality rate of more than 22% during floods. However, the increase in livestock comes at a cost. Households reduce spending on their homes, resulting in a drop in housing quality, which in turn increases the likelihood of house damage during floods.

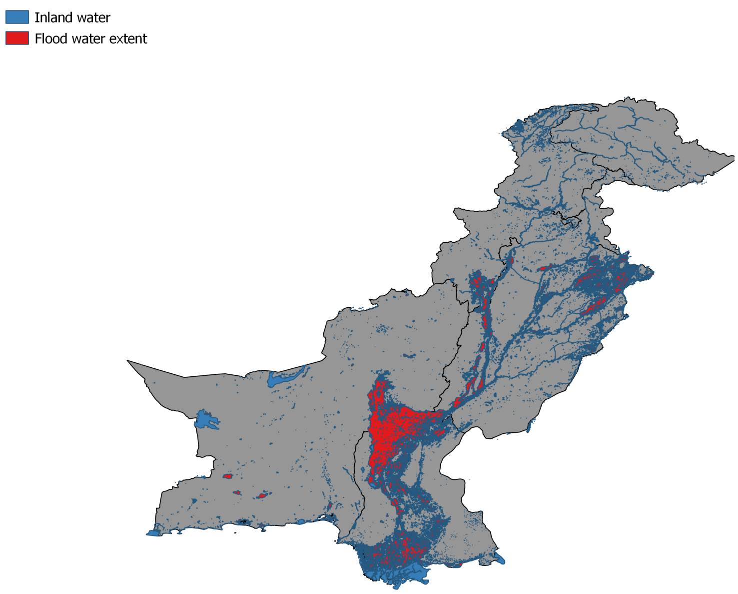
The setting of the program is Pakistan, a country that is extremely vulnerable to climate shocks. In August 2022, Pakistan experienced one of the deadliest episodes of floods, impacting more than 33 million people. Using the spatial variation in flood intensity, I find that while access to credit fosters growth under normal circumstances, particularly through increased livestock accumulation, it also introduces new vulnerabilities in the face of extreme shocks. In areas less affected by floods, households with access to credit continue to grow, accumulating more livestock. However, in high-flooded regions, the benefits of credit are wiped out by the 2022 floods, leaving them with fewer livestock relative to loan-ineligible households, worsened mental health, and greater housing damage. These effects remained persistent one year after the floods.

These findings carry significant policy implications. They demonstrate that simply improving access to credit may be insufficient for enhancing the well-being of communities in high-flood-risk areas. Such communities could face a trade-off between growth and resilience. While access to credit enables households to make investments that foster growth, it simultaneously reduces their resilience when faced with external shocks. A more comprehensive policy approach should incorporate an insurance component within the loan structure to mitigate the adverse effects of extreme events, such as floods, and safeguard both growth and resilience.

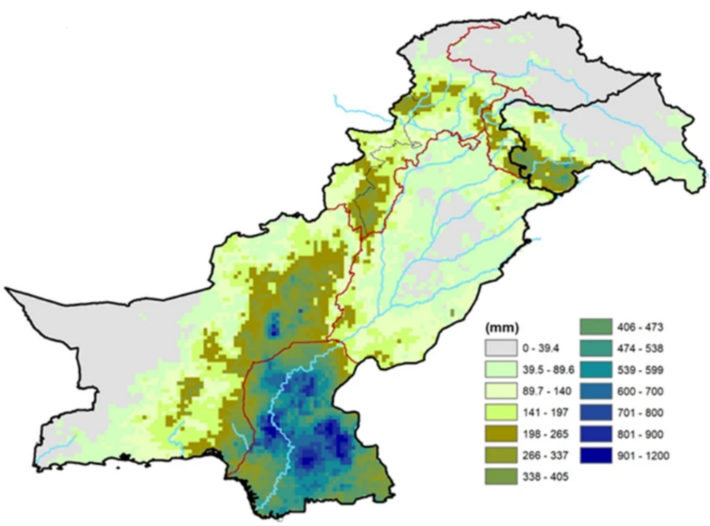
Another important policy implication is that communities vulnerable to climate shocks not only exhibit a high demand for credit but, more importantly, demonstrate a strong capacity for loan repayment. Before the floods, the default rates in the program were around 2%, comparable to microcredit repayment rates in the country. Loan repayments dropped during the floods, but around 80% of the loan principal that was outstanding during floods is successfully recovered within a year of floods. Moreover, the repayment rates on the overall loan portfolio from 2018 to 2022 are around 95%, comparable to those of other microfinance institutions. Despite the hesitancy among for-profit and non-profit institutions to extend credit to such vulnerable communities due to concerns over repayment, our findings suggest that it is feasible to offer loans, at least interest-free, with a high likelihood of repayment.

A Figures

Figure 1: Floodwaters and Rainfall in Pakistan from June-September 2022



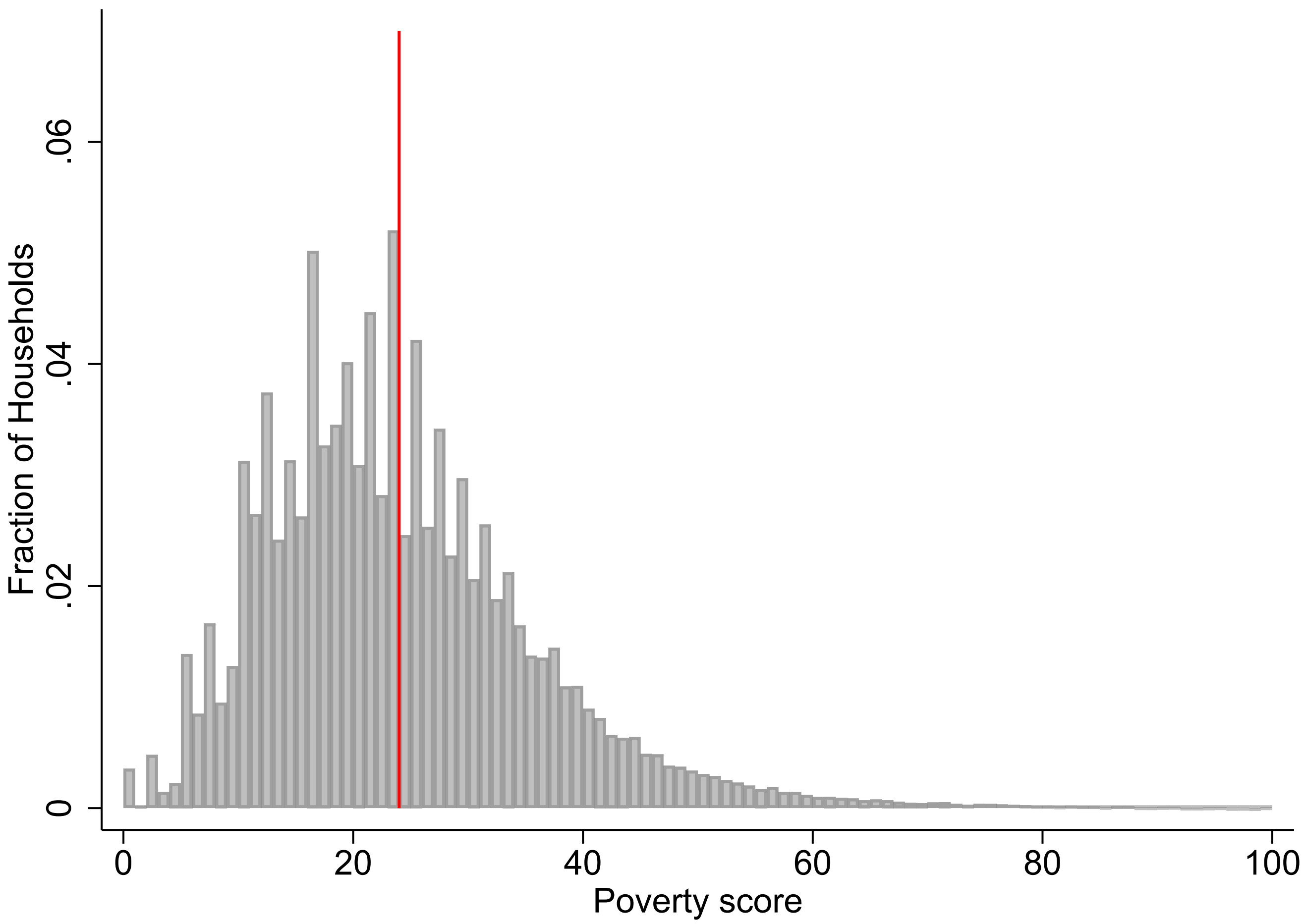
(a) Extent of floodwaters



(b) Rainfall

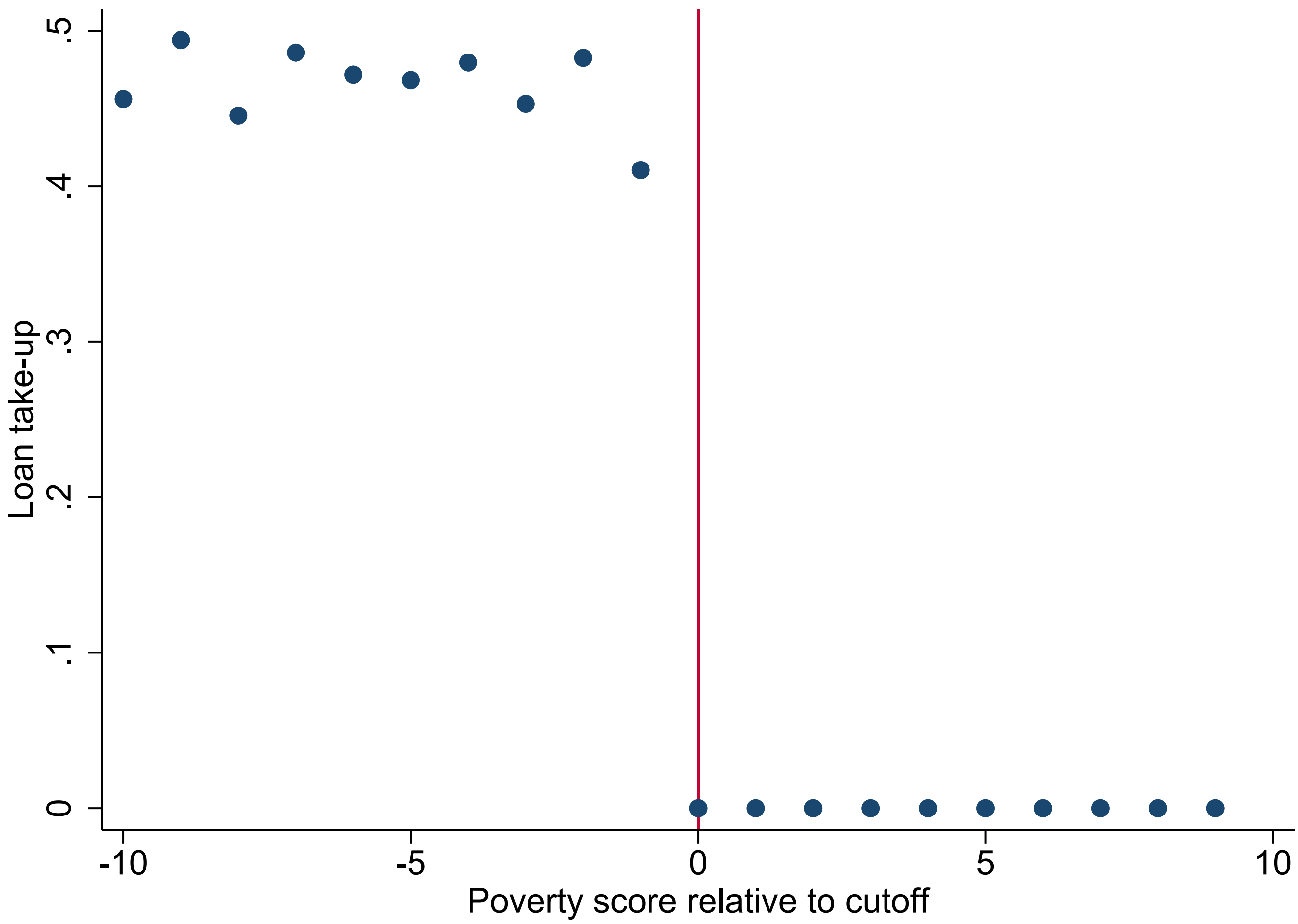
Notes: The figure shows the extent of floodwaters (Figure A) and the rainfall distribution (Figure B) in Pakistan during June-September 2022

Figure 2: Distribution of poverty score



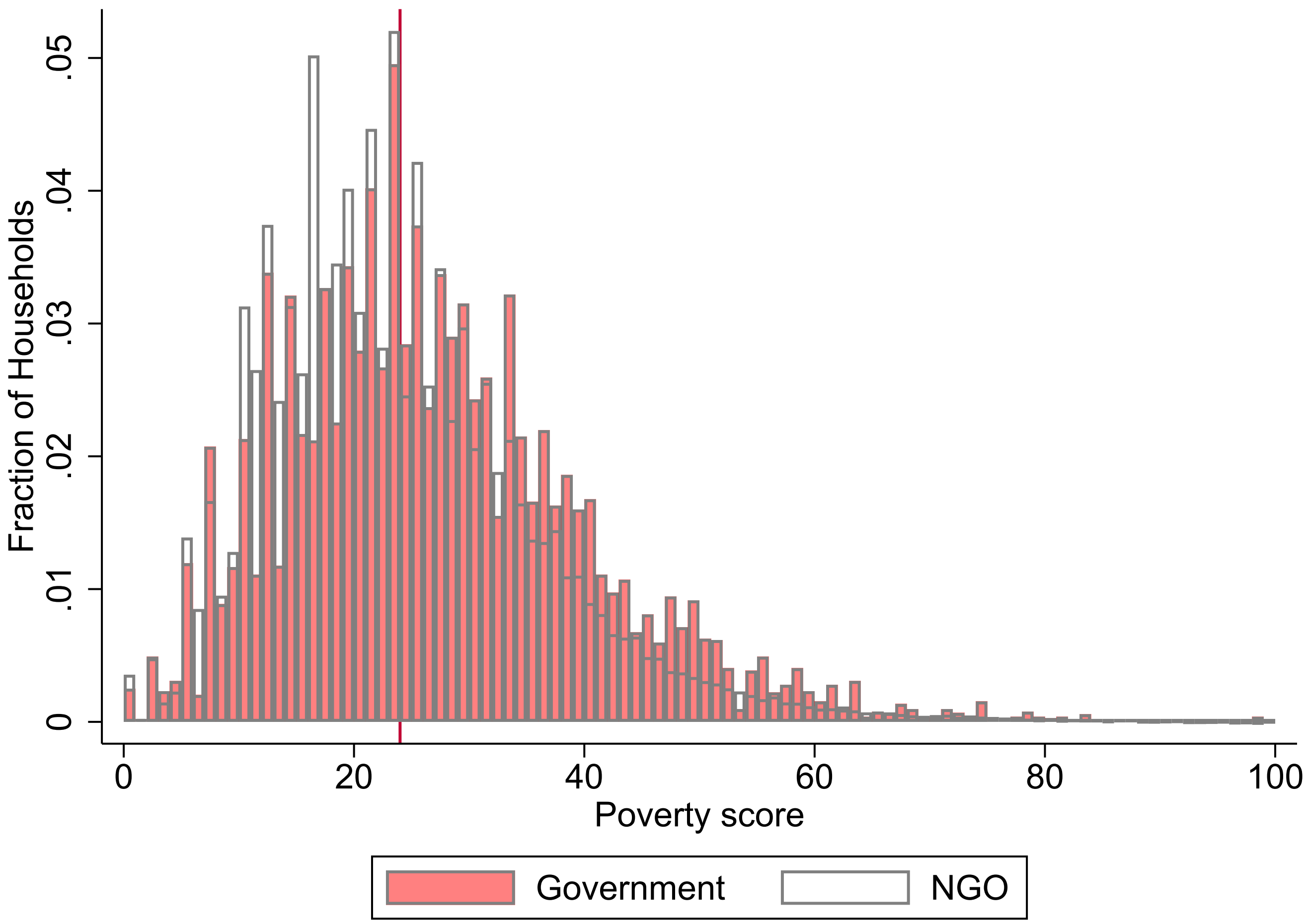
Notes: This figure shows the distribution of the poverty score for all the households in the eight districts where SUCCESS program is implemented. The red line at 24 represents the cutoff score for loans with households on the left being eligible for a loan.

Figure 3: Relevance - Compliance with the rule



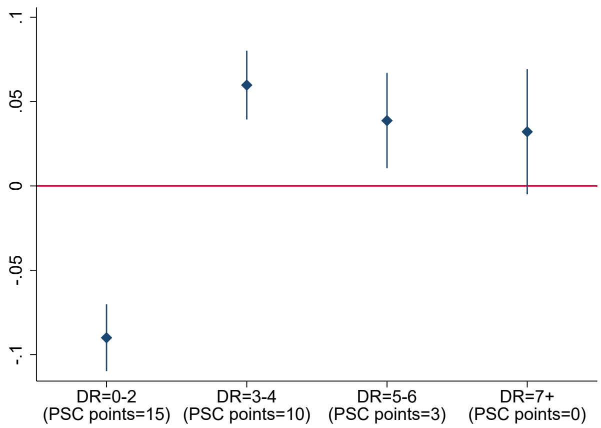
Notes: This figure shows the compliance of loan allocation with the eligibility rule. In this figure, I plot the average loan takeup on each poverty score relative to loan eligibility cutoff score. The sample include all households surveyed in the poverty assessment survey.

Figure 4: Validity - Distribution of poverty score

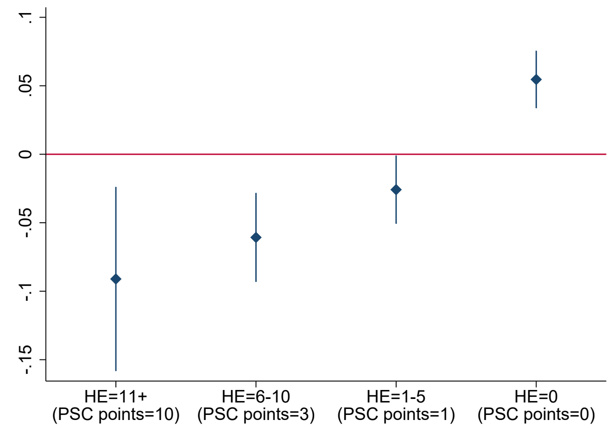


Notes: This figure shows the fraction of households for each value of the poverty score. The red histogram represents poverty scores derived from government-collected data for the same districts where the SUCCESS program was implemented and for the same year as the NGO data collection. The transparent histogram displays the distribution of poverty scores constructed using NGO data that is used to determine loan eligibility in the SUCCESS program.

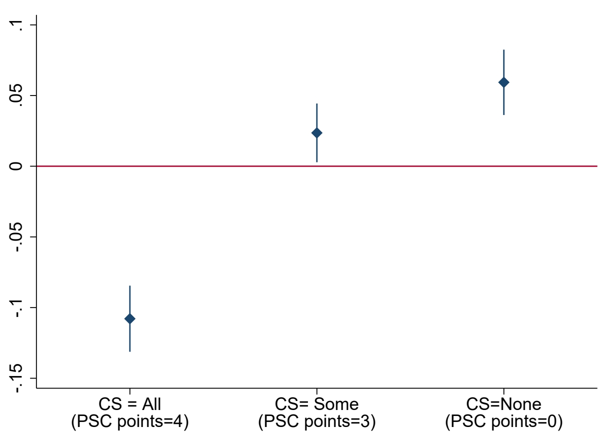
Figure 5: Validity - Likelihood of satisfying condition for people near the cutoff



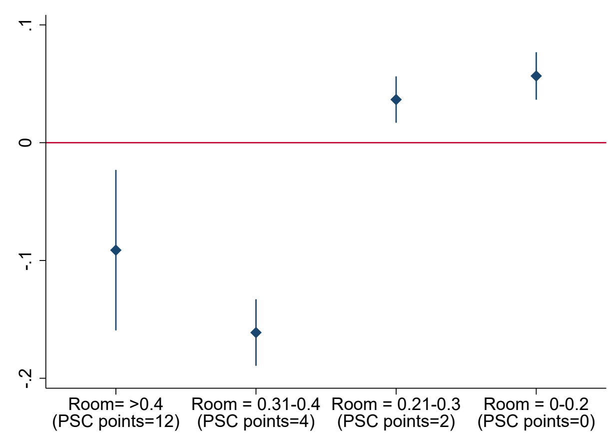
(a) Dependency Ratio (DR)



(b) Head Education (HE)



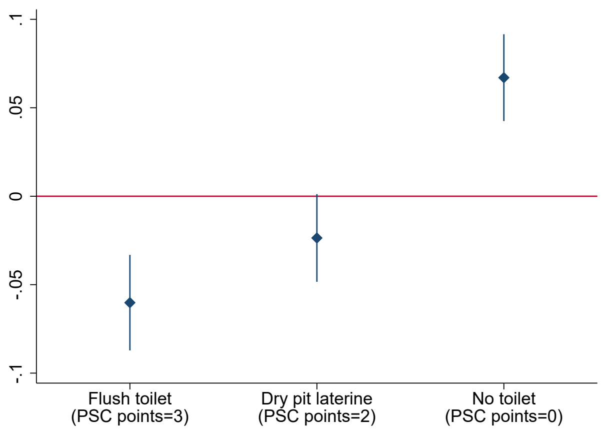
(c) Children in school (CS)



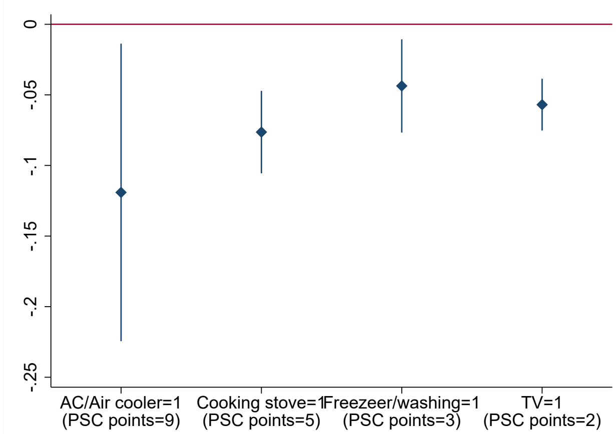
(d) Rooms per person

Notes: The figure presents coefficients and 95% confidence intervals from regressions estimating of being eligible for loans on taking certain value of each of the indicator used to construct the poverty score. The dependency ratio is defined as the number of household members either below the age of 16 or above 65. The x-axis shows the poverty score points associated with each value of the indicator. For instance, if a household has between 0 and 2 members below age 16 or above 65, it receives 15 points for that indicator The sample includes only households with a poverty score $\in \{22\ 25\}$ in the Matiari district where outcome surveys are conducted.

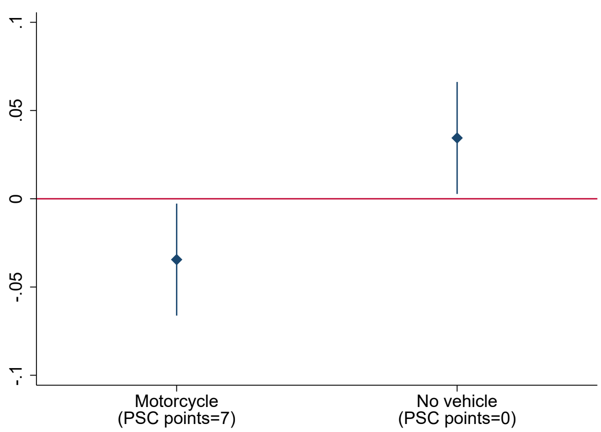
Figure 5: (Cont) Validity - Likelihood of satisfying condition for people near the cutoff



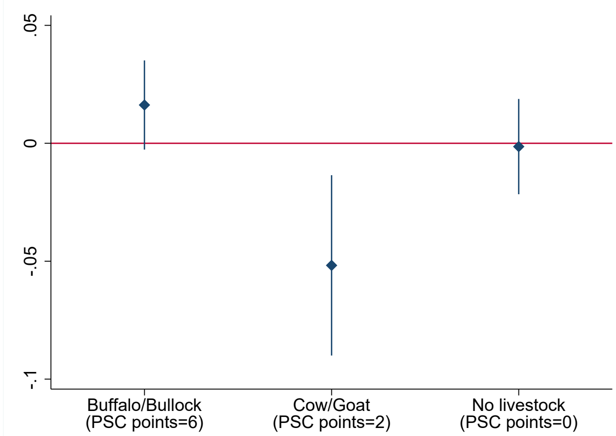
(a) Toilet



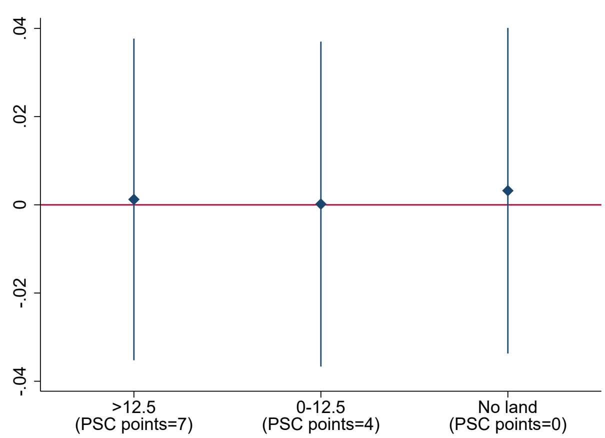
(b) Assets



(c) Vehicle



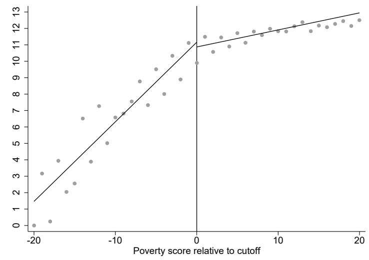
(d) Livestock



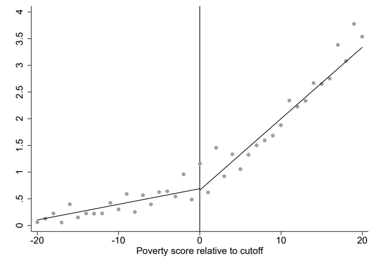
(e) Land

Notes: The figure presents coefficients and 95% confidence intervals from regressions estimating of being eligible for loans on taking certain value of each of the indicator used to construct the poverty score. The x-axis shows the poverty score points associated with each value of the indicator. For instance, if a household has a motorcycle, it receives 7 points for that indicator The sample includes only households with a poverty score $\in \{22\ 25\}$ in the Matiari district where outcome surveys are conducted.

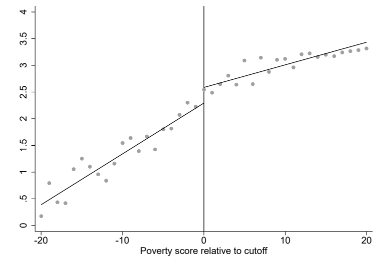
Figure 6: Validity - Continuity of indicator used to construct poverty score



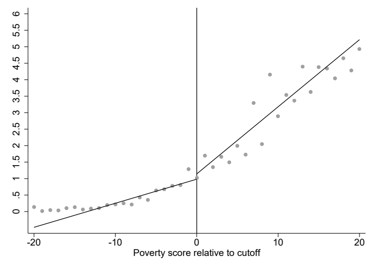
(a) Members below age 16 & above 65



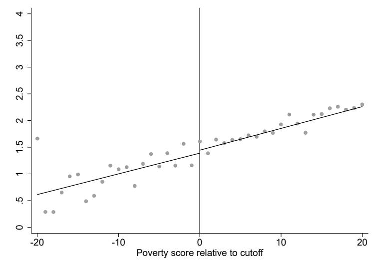
(b) Head Education



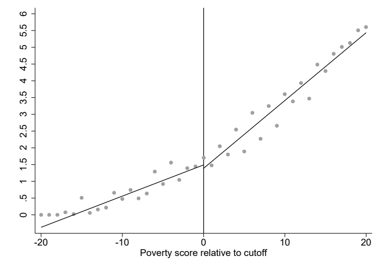
(c) Children in school



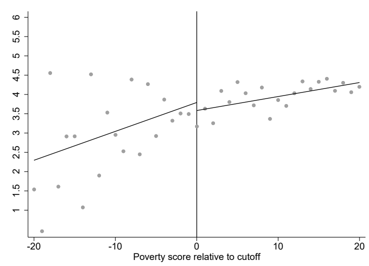
(d) Rooms per person



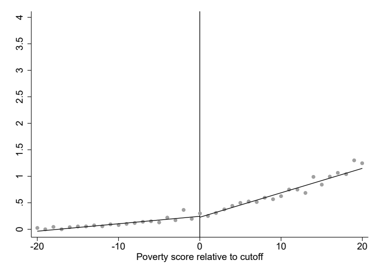
(e) Toilet(=1)



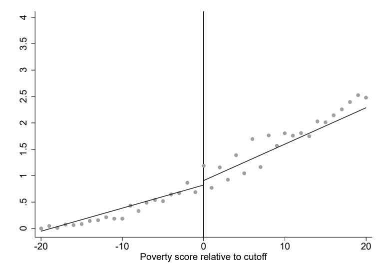
(f) Vehicle(=1)



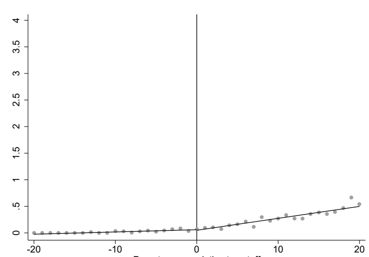
(g) Livestock(=1)



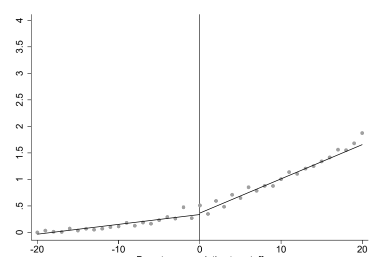
(h) Land(=1)



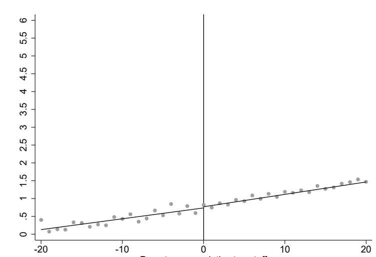
(i) Cooking stove(=1)



(j) AC(=1)



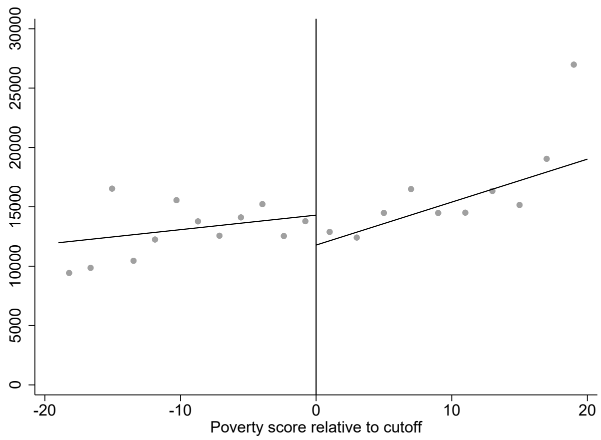
(k) Refrigerator(=1)



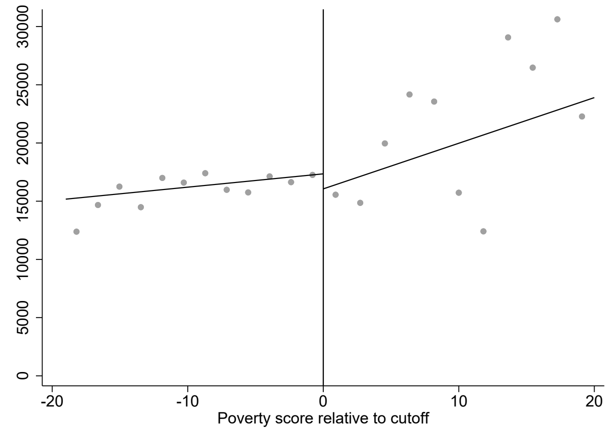
(l) TV(=1)

Notes: The panel shows the continuity of the variables used to construct the poverty score. This figure plots the average on each poverty score relative to loan eligibility cutoff score, within a bandwidth of 20. Poverty score to the left of 0 are eligible for getting a loan. Sample is restricted to the household residing in the Matiari district where outcome surveys are conducted.

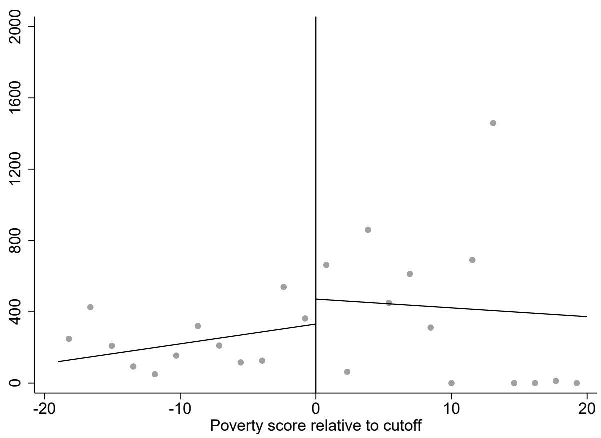
Figure 7: Validity - Continuity of other covariates at the baseline



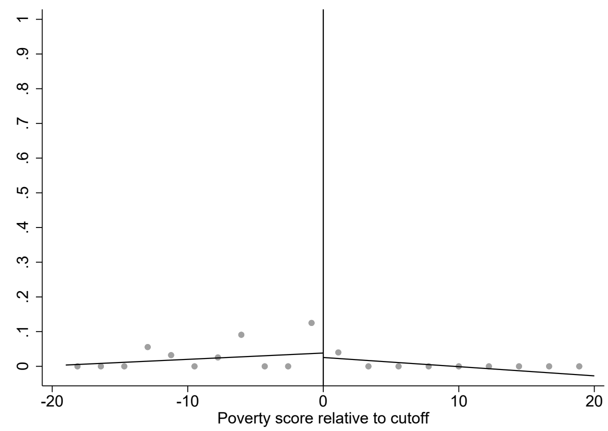
(a) Monthly expenditure (PKR)



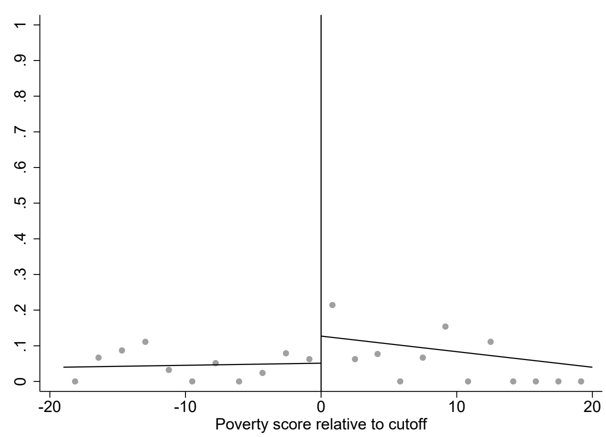
(b) Monthly income (PKR)



(c) Monthly livestock income (PKR)



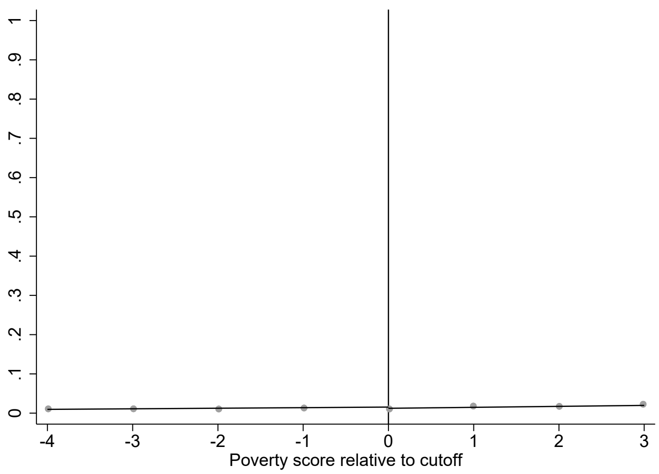
(d) Households with savings



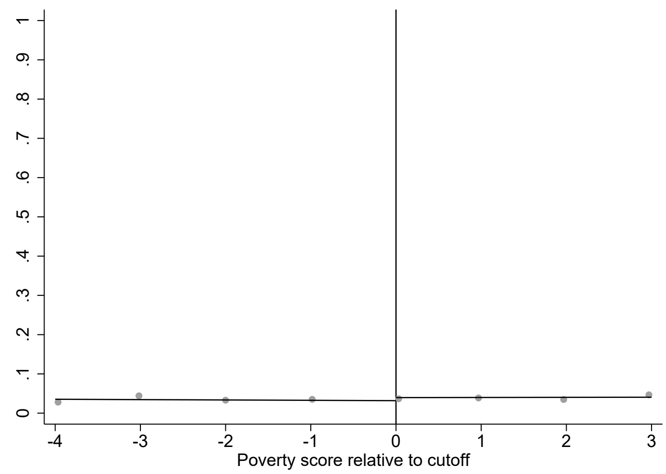
(e) Households with a loan

Notes: The panel shows the continuity of other covariates at the baseline. This figure plots the average on each poverty score relative to loan eligibility cutoff score, within a bandwidth of 20. Poverty score to the left of 0 are eligible for getting a loan. Sample is restricted to the household residing in the Matiari district where outcome surveys are conducted. The data is from a survey conducted by the NGO in 2018 as part of another project.

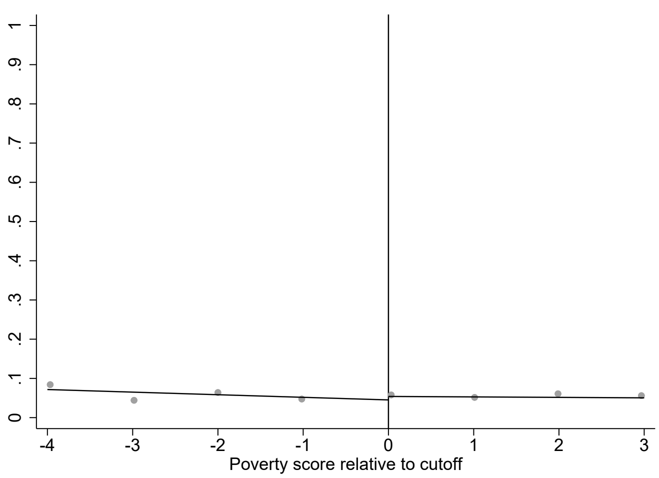
Figure 8: Results - Impact of loan access on ex-ante household investments



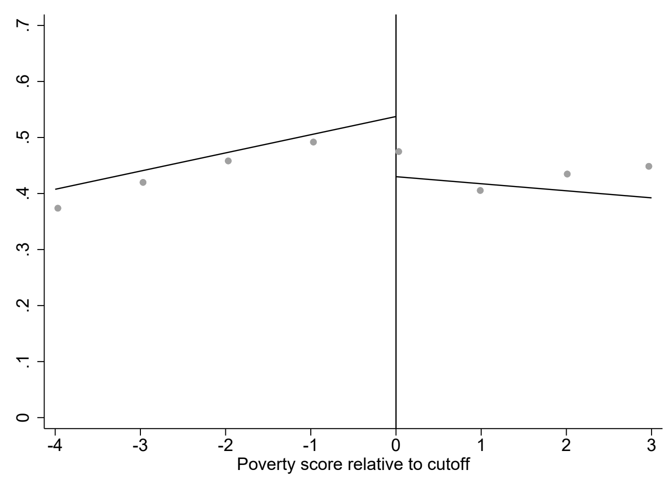
(a) Migration (=1)



(b) Business (=1)



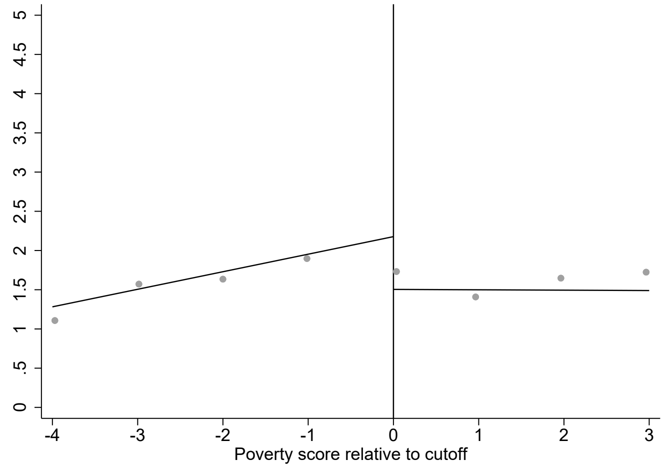
(c) Agriculture (=1)



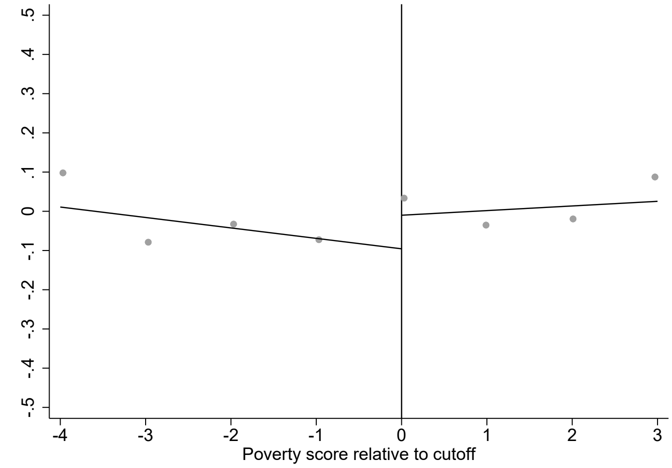
(d) Livestock (=1)

Notes: For each outcome reported in Table 5, this figure plots the average on each poverty score relative to loan eligibility cutoff score, within a bandwidth of 4. Scores to the left of 0 are eligible for getting a loan. For Figure 8a, the sample is at the individual level and includes all individuals above the age of 10. For all the outcomes, the sample is at the household level. Sample is restricted to the Matiari district where outcome surveys are conducted.

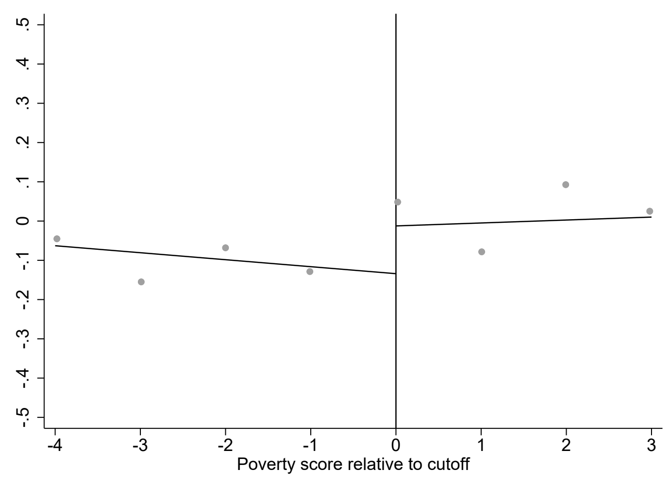
Figure 8: Results - Impact of loan access on ex-ante household investments



(e) Number of livestock



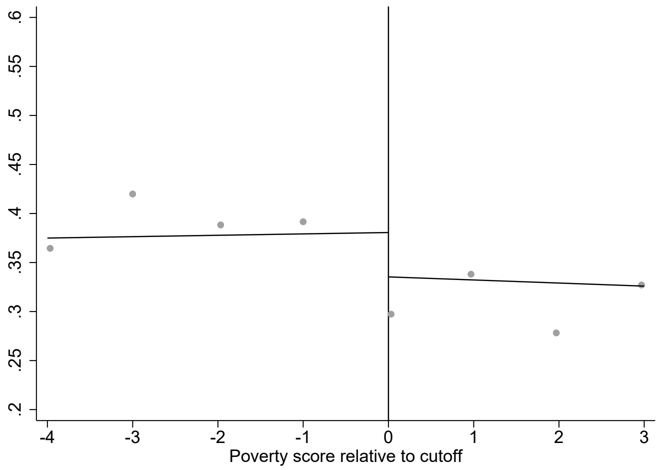
(f) Assets Index



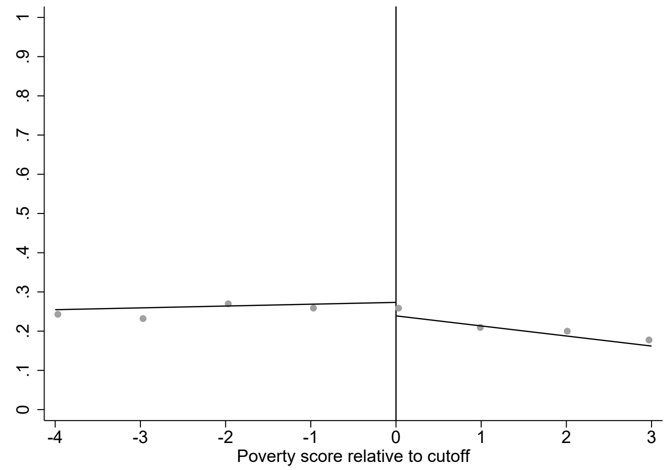
(g) Housing quality Index

Notes: For each outcome reported in Table 5, this figure plots the average on each poverty score relative to loan eligibility cutoff score, within a bandwidth of 4. Scores to the left of 0 are eligible for getting a loan. For Figure 8a, the sample is at the individual level and includes all individuals above the age of 10. For all the outcomes, the sample is at the household level. Sample is restricted to the Matiari district where outcome surveys are conducted.

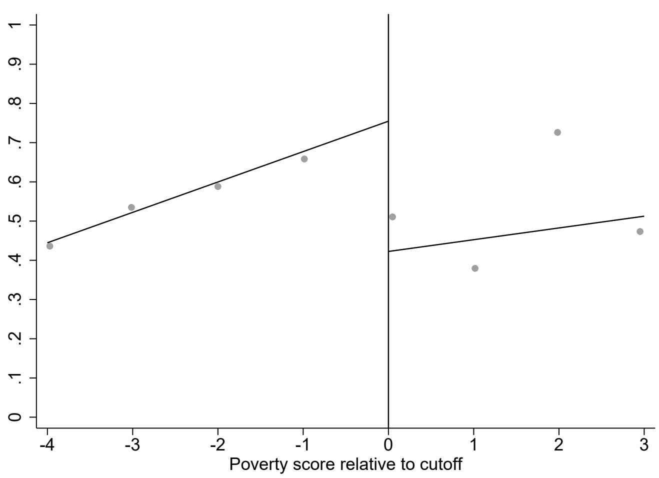
Figure 9: Results - Flood damages by loan eligibility status



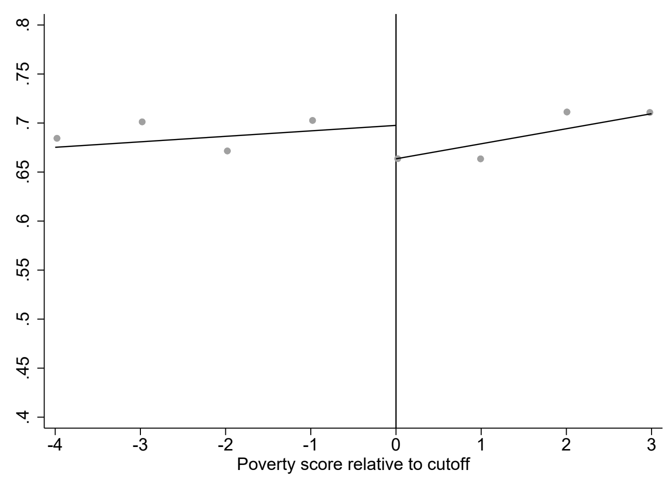
(a) Relocated (=1)



(b) Livestock died (=1)



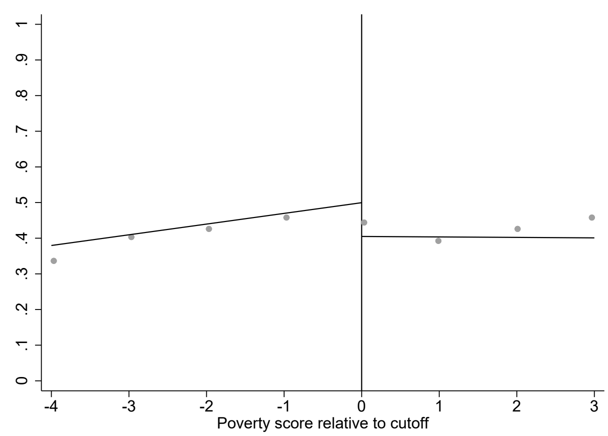
(c) Number of Livestock died



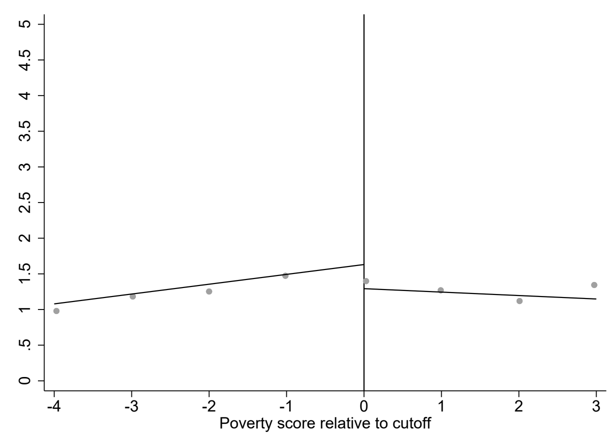
(d) House damaged (=1)

Notes: For each outcome reported in Table 7, this figure plots the average on each poverty score relative to loan eligibility cutoff score, withing a bandwidth of 4. Poverty score to the left of 0 are eligible for getting a loan. Sample is restricted to the Matiari district where outcome surveys are conducted.

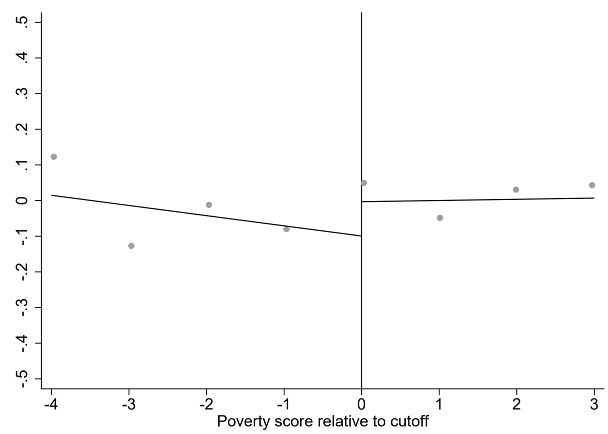
Figure 10: Results - Impact of loan access on resilience and welfare after the floods



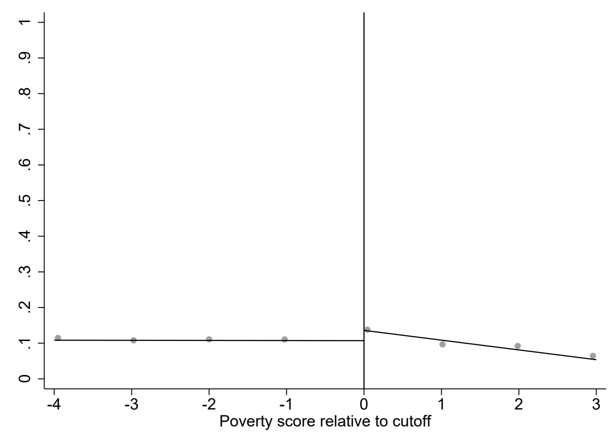
(a) Livestock (=1)



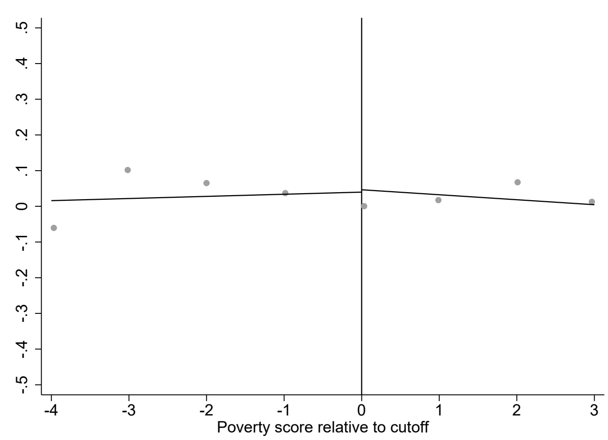
(b) Number of livestock



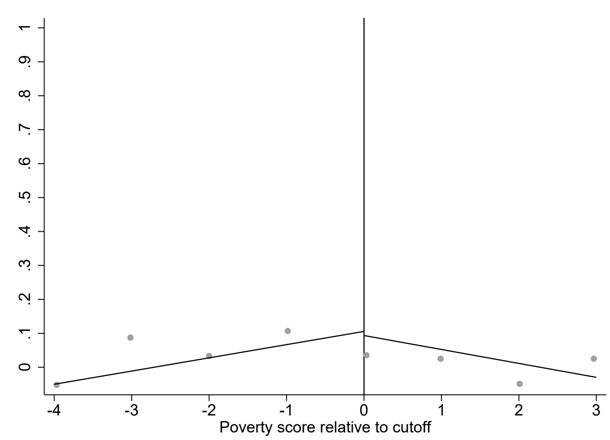
(c) Asset Index



(d) Repairs (=1)



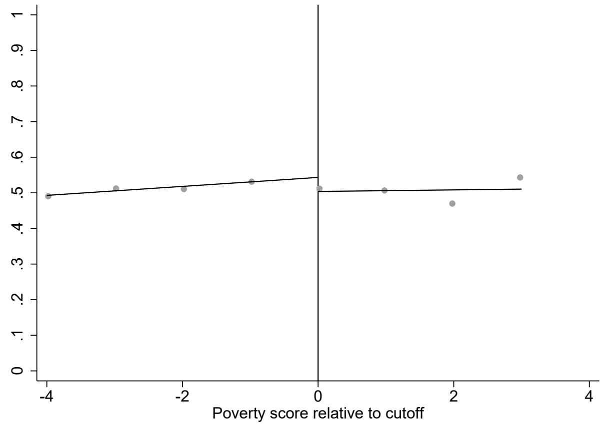
(e) Food insecurity Index



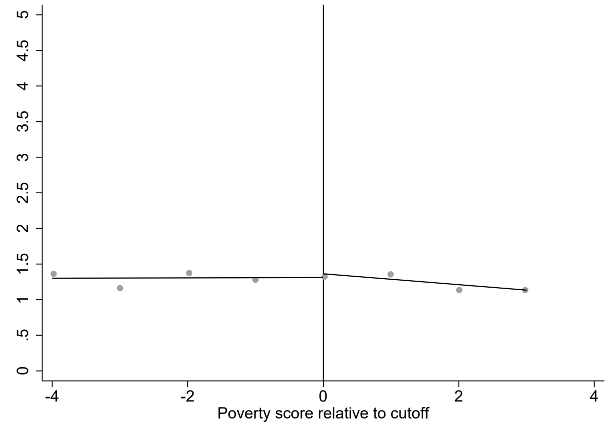
(f) Mental health Index

Notes: For each outcome reported in Table 8, this figure plots the average on each poverty score relative to loan eligibility cutoff score, withing a bandwidth of 4. Poverty score to the left of 0 are eligible for getting a loan. Sample is restricted to the Matiari district where outcome surveys are conducted.

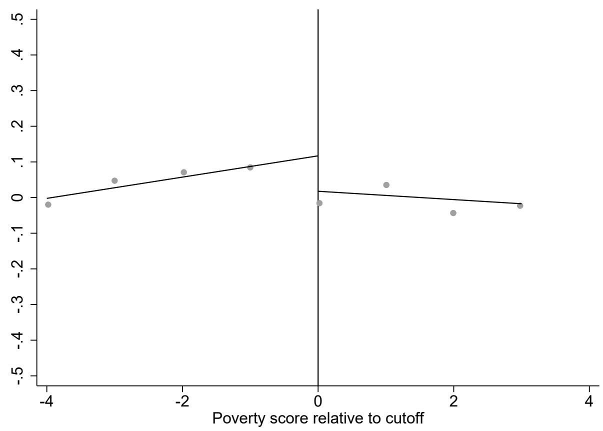
Figure 11: Results - Followup results after a year of floods



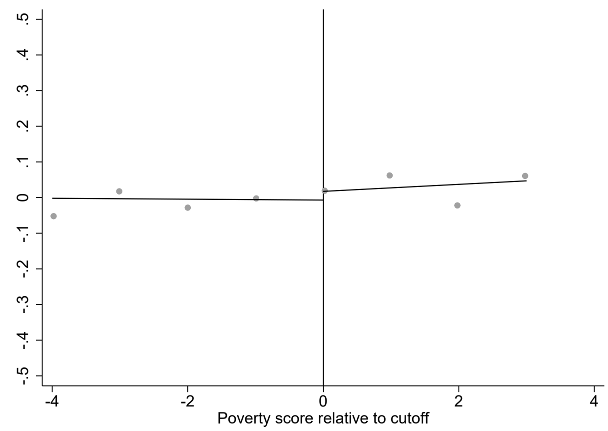
(a) Livestock (=1)



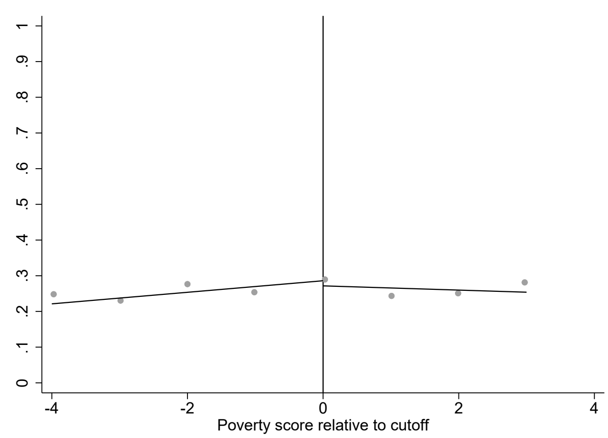
(b) Number of livestock



(c) Food insecurity Index



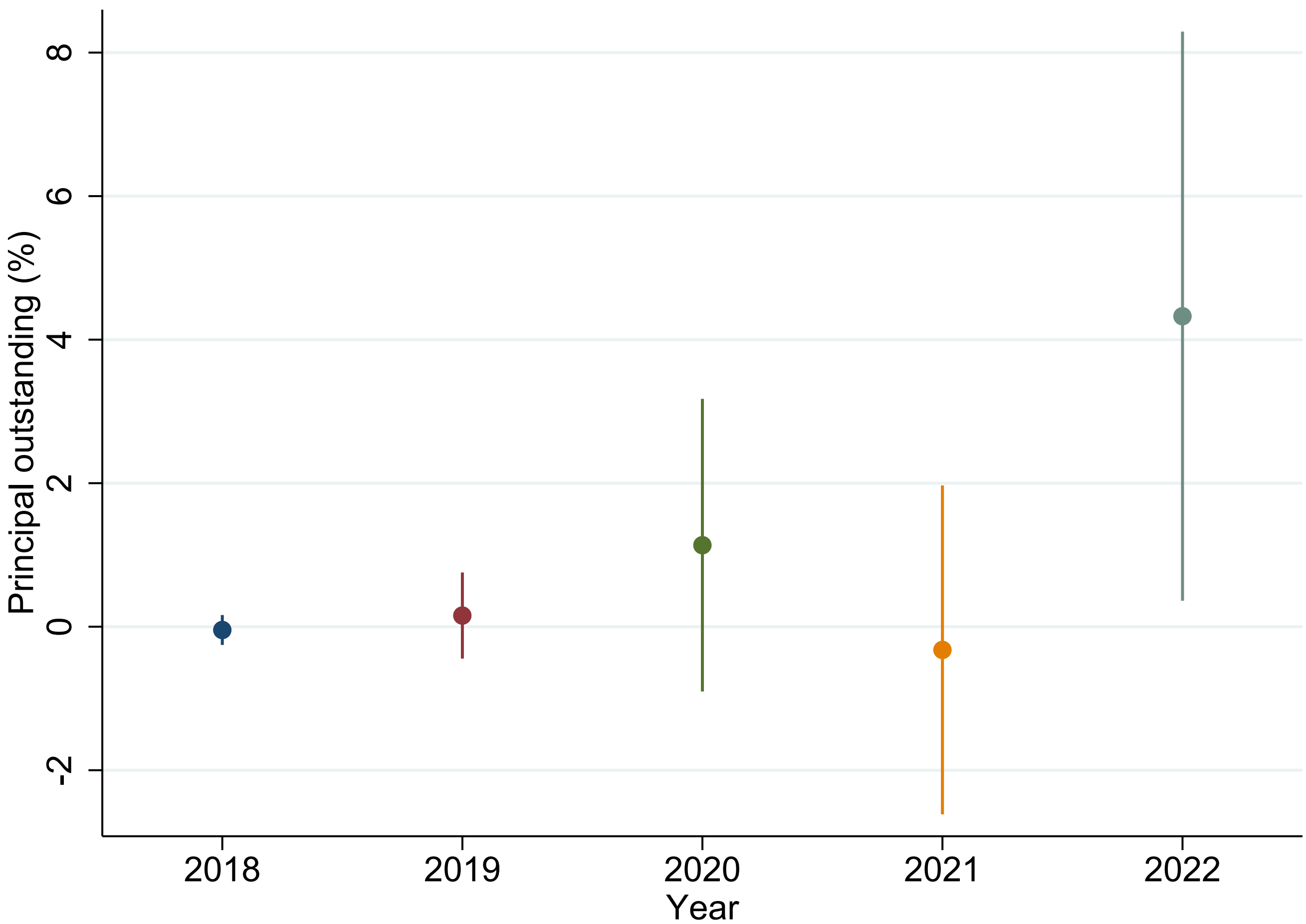
(d) Mental health Index



(e) Repairs (=1)

Notes: For each outcome reported in Table 10, this figure plots the average on each poverty score relative to loan eligibility cutoff score, withing a bandwidth of 4. Poverty score to the left of 0 are eligible for getting a loan. Sample is restricted to the Matiari district where outcome surveys are conducted.

Figure 12: Principal due by flood intensity



Notes: This figure shows the coefficients and the 95% confidence interval from estimating a regression of loan principal past the due date and the flood intensity for each year. The sample is restricted to all households who have taken a loan with a due date before April 2023. All regressions include union council fixed effects. Standard errors are clustered at the village level.

B Tables

Table 1: Summary statistics - SUCCESS districts

	Matiari	Sujawal	Tando Allahyar	Tando Muhammad Khan
Members	3.57	3.65	3.45	3.52
Head education	2.92	1.50	2.45	2.08
Children	2.31	2.25	2.20	2.20
Children schooling	0.87	0.50	0.77	0.61
Rooms	1.44	1.26	1.40	1.32
Land (=1)	0.12	0.31	0.11	0.22
Vehicle (=1)	0.01	0.01	0.01	0.01
Motorcycle (=1)	0.29	0.20	0.25	0.22
Livestock (=1)	4.11	1.86	4.10	2.74
Livestock (Num)	0.77	0.59	0.78	0.75
TV (=1)	0.42	0.09	0.33	0.21
Poverty score	26.32	20.56	25.33	23.10

Notes: This table presents the mean values for the 12 indicators used to construct the poverty score, with the sample restricted to the four districts where the SUCCESS program was implemented. Among these, the district of Matiari is where we conducted our outcome surveys.

Table 2: Validity - Attrition in the surveys

	High Flooded				Low flooded			
	Loan eligibles	Loan ineligibles	Diff	p-val	Loan eligibles	Loan ineligibles	Diff	p-val
	Panel A: Attrition in outcome survey							
Survey Completed	0.94	0.92	-0.01	0.74	0.92	0.93	-0.01	0.48
Attrited	0.06	0.07	0.01	0.97	0.08	0.07	0.01	0.33
Migrated	0.03	0.05	-0.01	0.66	0.04	0.04	-0.01	0.49
Not found	0.03	0.03	0.02	0.68	0.05	0.02	0.02***	0.03
	Panel B: Attrition in the followup survey							
Survey Completed	0.81	0.81	-0.01	0.18	0.95	0.96	-0.01	0.29
Attrited	0.19	0.19	0.01	0.18	0.05	0.04	0.01	0.29
Migrated	0.02	0.01	0.01	0.38	0.03	0.02	0.01	0.18
Not found	0.02	0.01	0.01*	0.08	0.02	0.02	0.01	0.49
Not Attempted	0.15	0.17	0.01	0.33	0.00	0.00	0.00	.

Notes: This table reports the attrition rates in the outcome surveys. Panel A reports attrition in the outcome survey conducted right after the floods (December 2022). Panel B reports attrition in the followup survey conducted after a year of floods. Column 1 and 2 reports the means for loan-eligibiles and loan-ineligibles in high-flooded villages. Column 3 is the difference between loan-eligibles and loan-ineligibles in the high-flooded villages estimated with a union council fixed effect. Column 4 gives us the p-value of the difference being different from zero. Column 5 and 6 reports the means for loan-eligibles and loan-ineligibles in the low-flooded villages. Column 7 is the difference between loan-eligibles and loan-ineligibles in the low-flooded villages estimated with a union council fixed effect. Column 8 gives us the p-value of the difference being different from 0.
***=significant at 1%, **=significant at 5%; *=significant at 10%

Table 3: Validity - Balance between High and low flooded villages

	Diff	p-val	Obs
Demographics			
Members	-0.07	0.38	78196.00
Head education	-0.29	0.18	78196.00
Children	-0.03	0.56	78196.00
Children schooling	-0.15***	0.00	78196.00
Rooms	-0.04	0.17	78196.00
Assets			
Land (=1)	-0.01	0.66	78196.00
Vehicle (=1)	-0.00	0.43	78196.00
Motorcycle (=1)	0.02	0.28	78196.00
TV (=1)	0.17	0.40	78196.00
Livestock			
Livestock (=1)	-0.00	0.86	78196.00
Livestock (Num)	0.01	0.63	78196.00
PSC and Loans			
Poverty score	-0.00	1.00	78196.00
Loan eligible	-0.01	0.58	78196.00
Loan Taken	-0.01	0.29	78196.00
Population	-38.10	0.73	102.00
Co membership & packages			
Membership	0.01	0.80	102.00
Grants	0.01	0.31	102.00
Skills	0.00	0.88	102.00
MHI	-0.00	0.71	102.00
Defaults			
Defaults	0.02	0.11	15796.00

Notes: The table shows the balance between the high- and low-flooded villages. Difference is calculated with union council fixed effects. Sample is restricted to all households in the Matiari district where outcome surveys are conducted. Standard errors are clustered at the village level

***=significant at 1%, **=significant at 5%; *=significant at 10%

Table 4: Relevance - Loan takeup & Repayments

	SUCCESS loan	SUCCESS Loan (Amount)	Bank loan	Family loan	shop loan	Loan past due (%)
	(1)	(2)	(3)	(4)	(5)	(6)
Loan RD	0.464***	5744.898***	-0.000	-0.005	0.002	0.021***
	(0.010)	(166.654)	(0.003)	(0.013)	(0.009)	(0.003)
Observations	40,100	40,100	3,218	3,218	3,218	28,398
Control mean	0.000	0.000	0.010	0.100	0.050	0.000

Notes: This table reports SUCCESS loan take-up, repayment and their impact on other forms of borrowing. The dependent variable includes whether the household has taken a SUCCESS loan, SUCCESS loan amount (zero for non borrowers) in Pakistani rupees, whether households has taken a loan from other banks, whether households has taken a loan from family and friend, whether households has taken a loan from shop keeper loans, and the percentage of SUCCESS loan amount that is past the due date (restricted to loans with a due date up to August 2022). The sample in the first two columns includes all COs where at least one member has taken a SUCCESS loan. The sample in the remaining columns is restricted to households that were surveyed in the outcome surveys. All regressions include village fixed effects. Standard errors are clustered at the village level.
***=significant at 1%, **=significant at 5%; *=significant at 10%

Table 5: Result - Impact of loan access on ex-ante household investments

	Migration(=1)	Business(=1)	Agri(=1)	Livestock(=1)	Livestock number	Non-livestock assets	House quality index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Loan RD	0.005	-0.006	0.004	0.060*	0.342*	-0.068*	-0.106***
	(0.005)	(0.013)	(0.015)	(0.035)	(0.190)	(0.035)	(0.030)
Observations	12,650	3,320	3,320	3,320	3,320	3,320	5,565
Control mean	0.020	0.040	0.050	0.440	1.560	-0.010	0.000

Notes: This table reports the RD coefficients prior to the floods, using a running variable of the poverty score relative to the loan cutoff. The dependent variables include whether any individual migrated, whether the household is running a business, whether the household engages in agriculture, whether the household owns livestock, the number of livestock, an index of non-livestock assets, and an index of housing quality. For Column (1), the sample is at the individual level and includes all individuals above the age of 10. For Columns (2)–(7), the sample is at the household level. The bandwidth is restricted to +/- 4, and standard errors are clustered at the village level. The RD specification is linear with a triangular kernel.
***=significant at 1%, **=significant at 5%, *=significant at 10%

Table 6: Result - Impact of floods

	Relocated (=1)	Livestock dead (=1)	Livestock dead (Num)	House damaged (=1)
	(1)	(2)	(3)	(4)
High-Flooded	0.086	0.107**	0.437***	0.063
	(0.075)	(0.042)	(0.114)	(0.043)
Observations	1,576	1,575	1,576	2,636
Control mean	0.280	0.170	0.230	0.650

Notes: This table reports the relocation and damages incurred during the 2022 floods. The coefficients are obtained from regressing the dependent variable against a binary indicator for flood intensity. The dependent variables include whether the households relocated during floods, whether the households has lost livestock, the number of livestock lost, whether the households incurred damages to the house. Sample is restricted to loan-eligible households in the Matiari district where the outcome surveys are conducted. All regressions include village fixed effects. Standard errors are clustered at the village level. ***=significant at 1%, **=significant at 5%; *=significant at 10%

Table 7: Result - Flood damages & relocation by loan eligibility status

	Relocated	Livestock died (=1)	Livestock died (Num)	House damaged
	(1)	(2)	(3)	(4)
Loan RD	0.051*	0.016	0.285***	0.034*
	(0.031)	(0.026)	(0.104)	(0.020)
Observations	3,271	3,270	3,271	5,565
Loan ineligible mean	0.320	0.220	0.460	0.680

Notes: This table reports the RD coefficients on relocation and damages damages incurred during the 2022 floods. The dependent variables include whether households relocated during the floods, whether households lost livestock, the number of livestock lost, and whether households incurred damages to their homes. The sample is restricted to loan-eligible households in the Matiari district, where the outcome surveys were conducted. All regressions include village fixed effects. The bandwidth is restricted to +/- 4, and standard errors are clustered at the village level.
***=significant at 1%, **=significant at 5%; *=significant at 10%

Table 8: Result - Impact of loan access on resilience & welfare after the floods

	Livestock (=1)	Livestock (Num)	Assets	Food insecurity	Mental Health	Repair
	(1)	(2)	(3)	(4)	(5)	(6)
Loan RD	0.058*	0.089	-0.069	-0.004	-0.089	-0.037
	(0.031)	(0.143)	(0.049)	(0.052)	(0.068)	(0.026)
Observations	3,270	3,271	3,271	3,271	3,205	1,912
Loan ineligible mean	0.420	1.310	-0.010	0.000	0.000	0.110

Notes: This table reports the RD coefficients on resilience and welfare after the floods. The dependent variables include whether the household owns livestock, the number of livestock, an index of non-livestock assets, an index of food insecurity, an index of mental health and whether the household has made any house repairs after the floods. Sample is restricted to loan-eligible households in the Matiari district where the outcome surveys are conducted. All regressions include village fixed effects. The bandwidth is restricted to +/- 4, and standard errors are clustered at the village level. The RD specification is linear with a triangular kernel.
***=significant at 1%, **=significant at 5%, *=significant at 10%

Table 9: Heterogeneity - Impact of loan access on resilience & welfare after the floods by flood intensity

	House damaged	Relocated	Livestock	Livestock number	Non-livestock assets	Food insecurity	Mental Health	Repair
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Loan eligible (γ)	0.026	0.052	0.094**	0.364*	-0.099	0.006	-0.066	-0.034
	(0.034)	(0.045)	(0.046)	(0.188)	(0.079)	(0.069)	(0.094)	(0.044)
Floodxloan Eligible (δ)	0.032	0.007	-0.070	-0.458*	0.016	0.025	-0.115	-0.000
	(0.045)	(0.056)	(0.063)	(0.272)	(0.096)	(0.100)	(0.130)	(0.054)
Observations	5,565	3,272	3,271	3,272	3,272	3,272	3,206	1,913
Control mean	0.680	0.320	0.420	1.310	-0.010	0.000	0.000	0.110
$\gamma + \delta$	0.060	0.060	0.020	-0.090	-0.080	0.030	-0.180	-0.030
p-value($\gamma + \delta$)	0.050	0.080	0.560	0.640	0.130	0.660	0.040	0.270

Notes: This table reports the heterogeneous impact of access to loans on household resilience and welfare by flood intensity. The estimates are coefficients from specification 2. The dependent variables include whether households incurred damages to their homes, whether households relocated during the floods, whether the the household owns livestock, the number of livestock, an index of non-livestock assets, an index of food insecurity, an index of mental health and whether the household has made any house repairs after the floods. Sample is restricted to loan-eligible households in the Matiari district where the outcome surveys are conducted. All regressions include union council fixed effects. The bandwidth is restricted to +/- 4, and standard errors are clustered at the village level. The RD specification is linear with a triangular kernel.
***=significant at 1%, **=significant at 5%, *=significant at 10%

Table 10: Results - Followup results on resilience & welfare after a year of floods

	Livestock (=1)	Livestock (Num)	Food insecurity	Mental Health	Repair
	(1)	(2)	(3)	(4)	(5)
Loan RD	0.044	0.019	0.064	-0.037	-0.023
	(0.035)	(0.125)	(0.051)	(0.050)	(0.036)
Observations	2,893	2,893	2,893	2,893	1,973
Loan ineligible mean	0.510	1.270	0.000	0.030	0.260

Notes: This table reports the RD coefficients on resilience and welfare in the follow up survey conducted after a year of the floods. The dependent variables include whether the household owns livestock, the number of livestock, an index of food insecurity, an index of mental health and whether the household has made any house repairs after the floods. Sample is restricted to loan-eligible households in the Matiari district where the outcome surveys are conducted. All regressions include village fixed effects. The bandwidth is restricted to +/- 4, and standard errors are clustered at the village level. The RD specification is linear with a triangular kernel.

***=significant at 1%, **=significant at 5%, *=significant at 10%

Table 11: Heterogeneity - Impact of loan access on resilience & welfare after one year of floods by flood intensity

	Livestock(=1)	Livestock number	food insecurity	Mental health	Repairs
	(1)	(2)	(3)	(4)	(5)
Loan eligible (γ)	0.096*	0.242	0.039	0.029	-0.042
	(0.049)	(0.197)	(0.029)	(0.076)	(0.049)
Floodxloan Eligible (δ)	-0.125*	-0.506**	-0.019	-0.158	0.049
	(0.070)	(0.247)	(0.040)	(0.100)	(0.069)
Observations	2,893	2,893	2,893	2,893	1,973
Control mean	0.510	1.340	0.250	0.020	0.270
$\gamma + \delta$	-0.030	-0.260	0.020	-0.130	0.010
p-value($\gamma + \delta$)	0.560	0.080	0.460	0.050	0.890

Notes: This table reports the heterogeneous impact of access to loans on household resilience and welfare by flood intensity in the follow up survey. The estimates are coefficients from specification 2. The dependent variables include whether the household owns livestock, the number of livestock, an index of food insecurity, an index of mental health and whether the household has made any house repairs after the floods. Sample is restricted to loan-eligible households in the Matiari district where the outcome surveys are conducted. All regressions include village fixed effects. The bandwidth is restricted to +/- 4, and standard errors are clustered at the village level. The RD specification is linear with a triangular kernel.
***=significant at 1%, **=significant at 5%, *=significant at 10%

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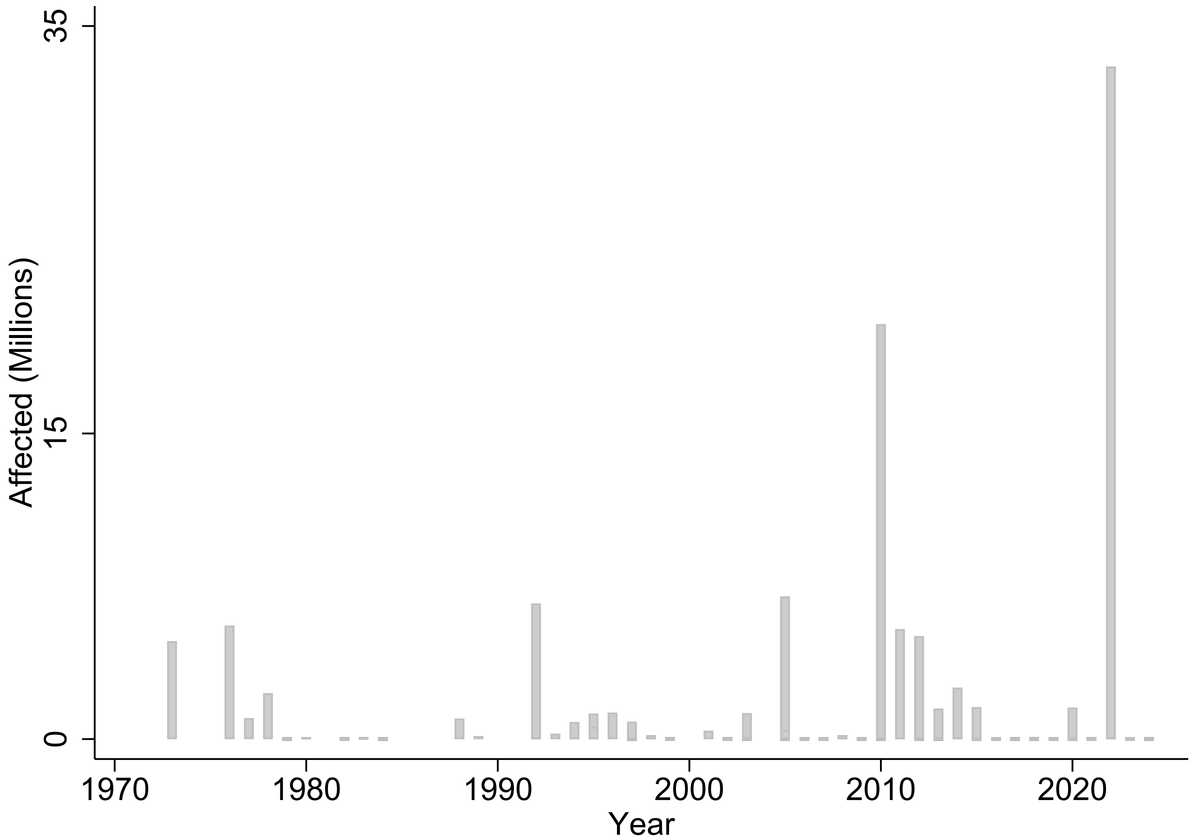
C Appendix Tables and Figures

Figure A1: Three-tiered Community Organizations

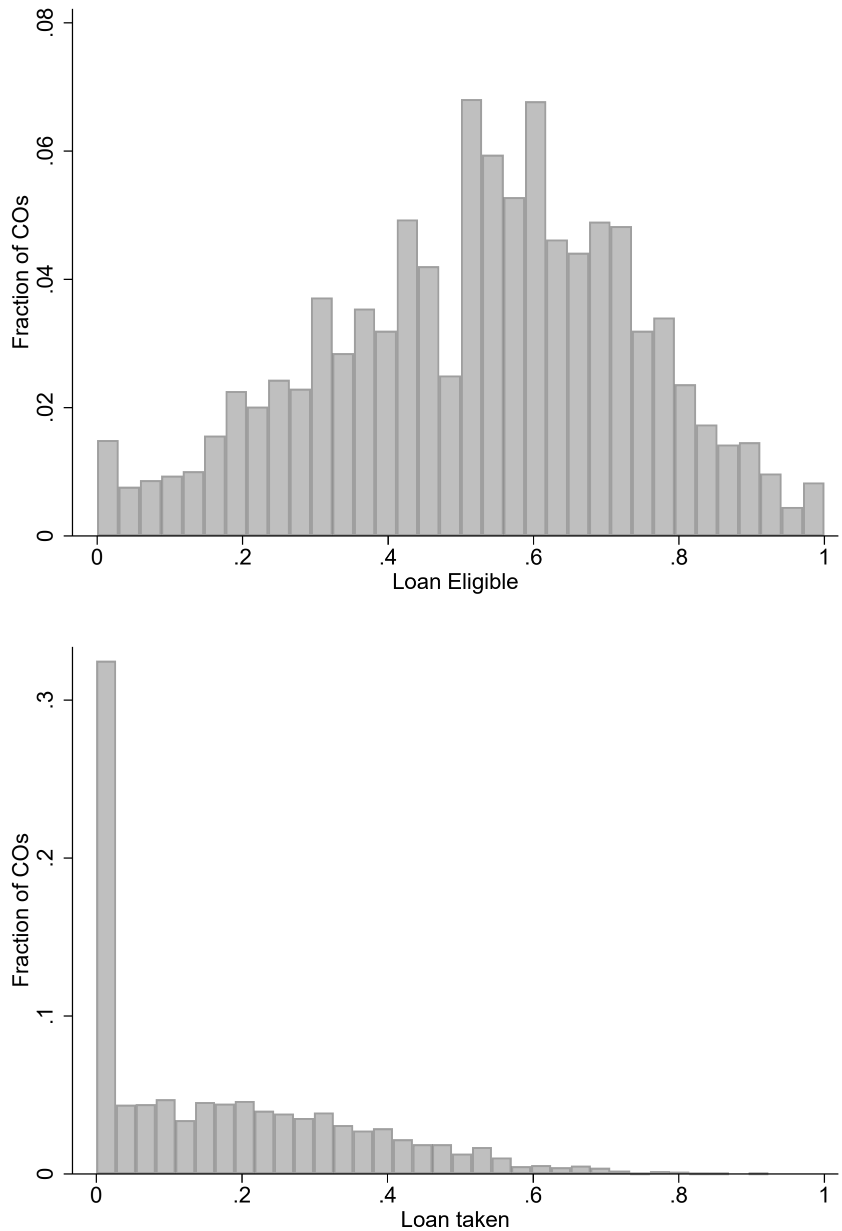
Notes: This figure highlights the major features of the three-tiered social mobilization approach of the RSPs.

Figure A2: Number of people affected by floods from 1970 to 2024



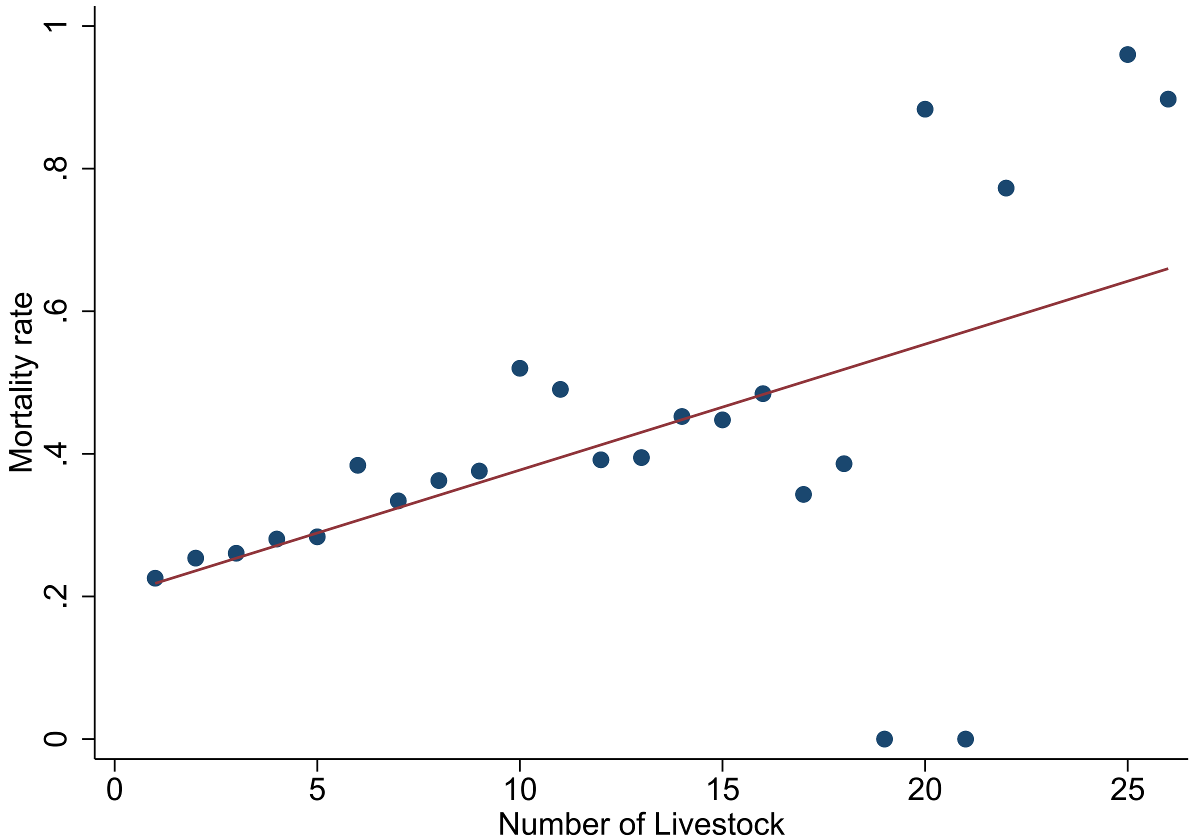
Source: EM-DAT database
Note: The figure shows the number of people affected by floods in Pakistan since 1970.

Figure A3: Distribution of Community organization (COs) by loan eligible and loan taken



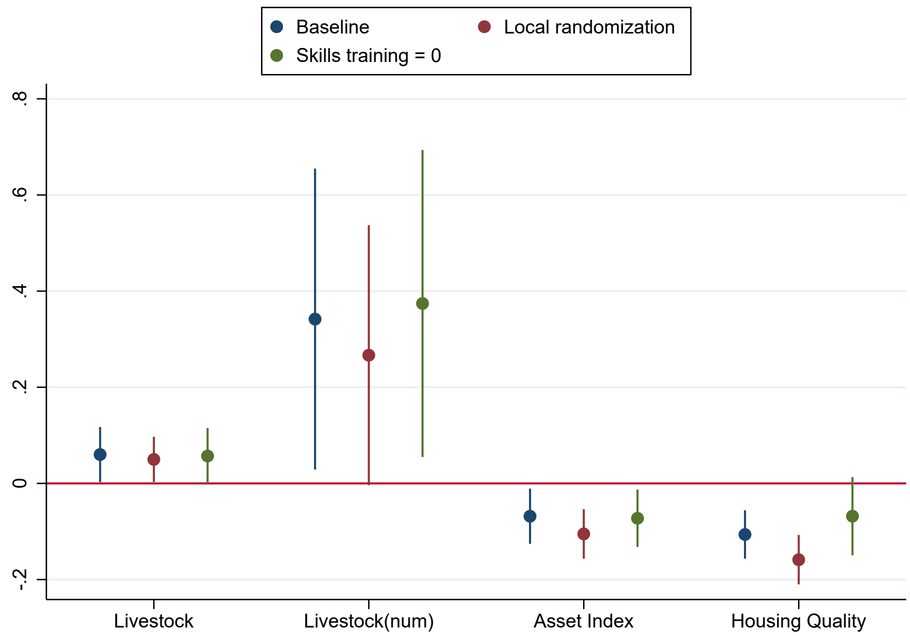
Notes: The figure shows the distribution of loan-eligible households within a CO (Figure a) and the distribution of the share of members who have taken a loan.

Figure A4: Livestock Mortality Rates by Herd Size

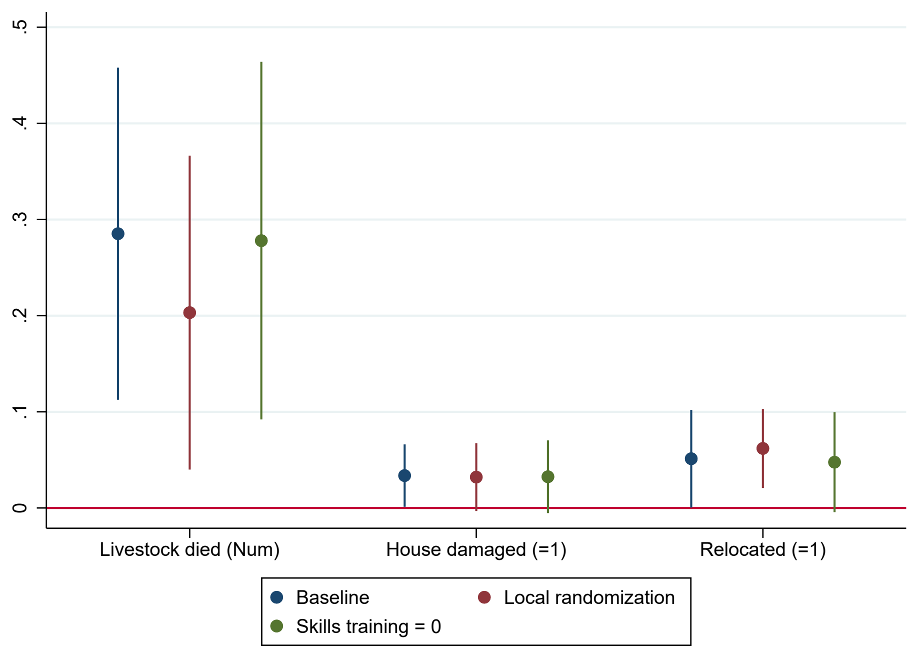


Note: The figure depicts the relationship between livestock mortality rates and the number of livestock owned.

Figure A5: Robustness checks for ex-ante outcomes and damages



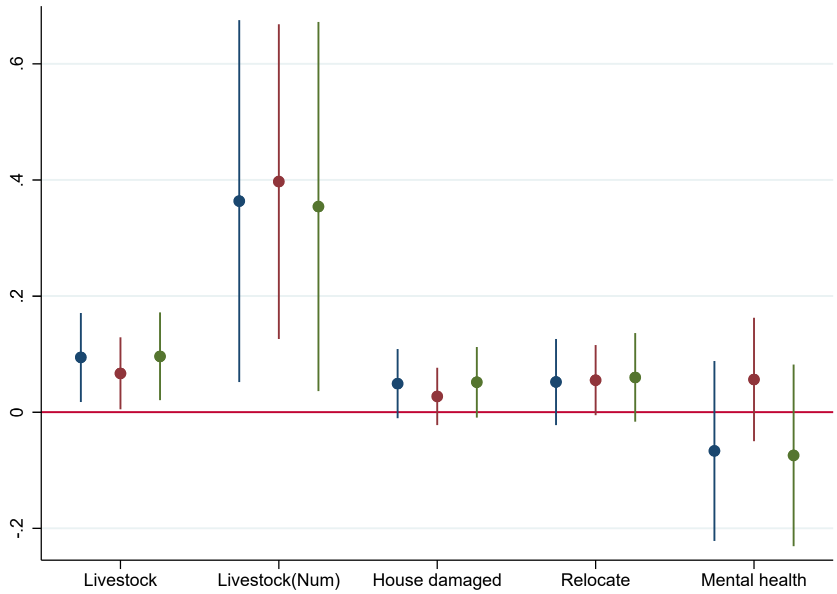
(a) Ex-ante ouctomes



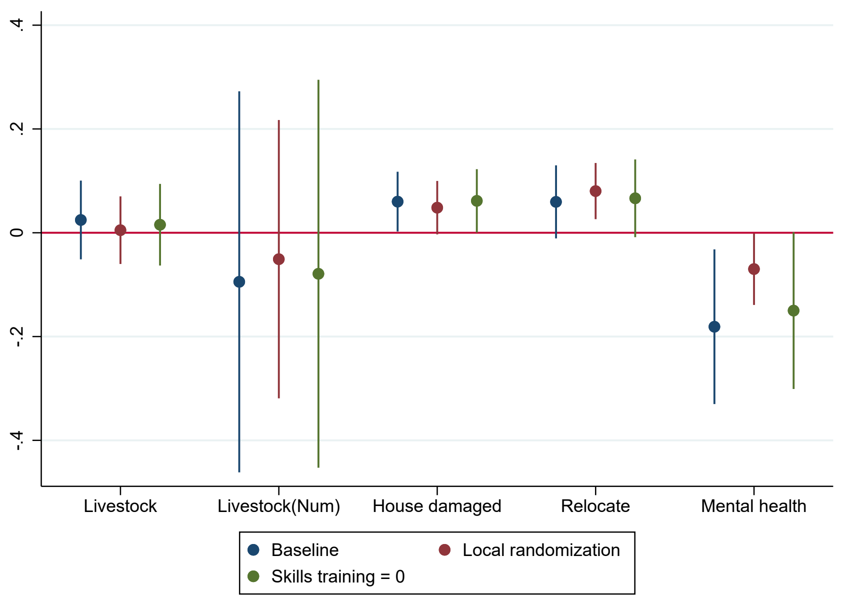
(b) Damages

Notes: These figures display the robustness checks for ex-ante outcomes and damages. Panel (a) shows robustness checks for the ex-ante outcome, as discussed in Table 5, while Panel (b) presents robustness checks for the damage outcome, as discussed in Table 7. The blue markers represent the estimates and 90% confidence intervals for the main RD specification (baseline). The red markers show the estimates and 90% confidence intervals using the local randomization approach, where the sample is restricted to households with a poverty score of 23 and 24. The green markers represent the estimates and 90% confidence intervals for the main RD specification, excluding households that received skills training.

Figure A6: Robustness checks for ex-post resilience and welfare outcomes using local randomization inference



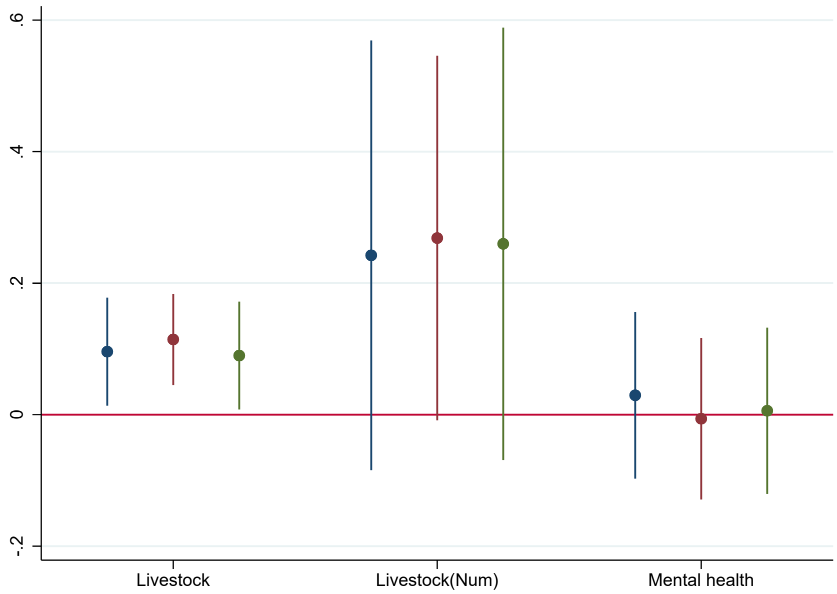
(a) Ex-post resilience & welfare - Low-flooded villages



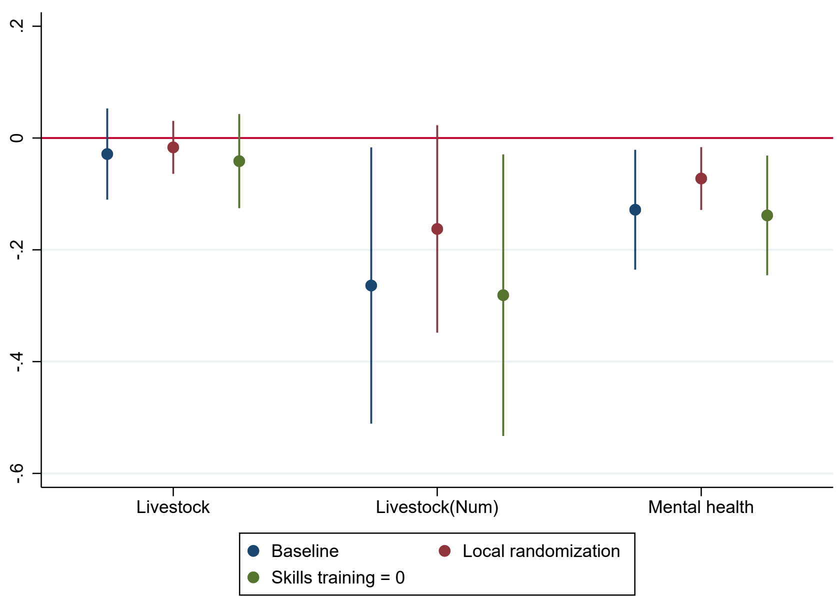
(b) Ex-post resilience & welfare - High-flooded villages

Notes: These figures display the robustness checks for ex-post resilience and welfare outcomes, as discussed in Table 9. Panel (a) shows robustness checks for the Low-flooded villages, while Panel (b) presents robustness checks for the High-flooded villages. The blue markers represent the estimates and 90% confidence intervals for the main RD specification (baseline). The red markers show the estimates and 90% confidence intervals using the local randomization approach, where the sample is restricted to households with a poverty score of 23 and 24. The green markers represent the estimates and 90% confidence intervals for the main RD specification, excluding households that received skills training.

Figure A7: Robustness checks for followup results using local randomization inference



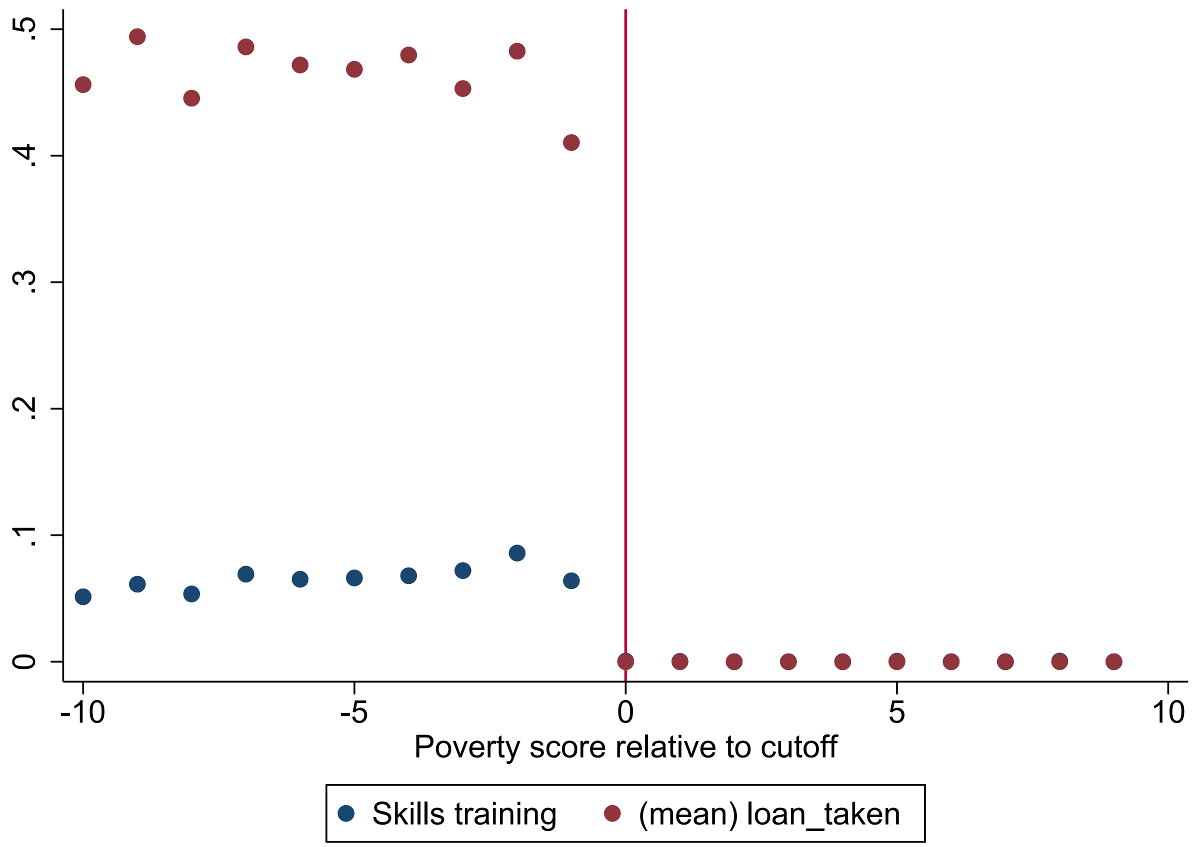
(a) Follow up results - Low-flooded villages



(b) Follow up results - High-flooded villages

Notes: These figures display the robustness checks from the follow-up survey, as discussed in Table 11. Panel (a) shows robustness checks for the Low-flooded villages, while Panel (b) presents robustness checks for the High-flooded villages. The blue markers represent the estimates and 90% confidence intervals for the main RD specification (baseline). The red markers show the estimates and 90% confidence intervals using the local randomization approach, where the sample is restricted to households with a poverty score of 23 and 24. The green markers represent the estimates and 90% confidence intervals for the main RD specification, excluding households that received skills training.

Figure A8: Skills training and loan take-up



Notes: This figure shows the share of eligible households that received skills training and the share of households that received loans. The blue dots represent the percentage of households that received skills training, while the red dots represent the mean share of households that took loans, both plotted relative to the poverty score cutoff.

Table A1: Comparison of districts where SUCCESS program was implemented with other districts in the province

	All districts	Diff	p-val
Paid work	0.49	-0.03	0.32
Read/Write	0.45	-0.04	0.33
Attended school	0.45	-0.03	0.41
Own Land	0.30	-0.07*	0.07
Own house	0.91	0.02	0.46
Rooms	1.83	-0.18	0.11
Own livestock	0.29	-0.13*	0.09
Livestock Num	1.15	-0.18	0.34
TV	0.36	0.05	0.58
Own Freezer	0.16	-0.00	0.92
Own AC or Cooler	0.02	0.00	0.85
Own Motorcycle	0.29	-0.03	0.51
Own Car	0.02	-0.00	0.43
Own Tractor	0.02	-0.00	0.74
Own Cooking stove	0.13	0.05	0.23

Notes: This table presents the comparison of districts where SUCCESS program was implemented to other districts of the province. ***=significant at 1%, **=significant at 5%; *=significant at 10%

Table A2: Variation in rainfall data and floodwaters depth

	Water enter	Water_20	Water_40	Water_60	Water_80	Water_100
	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall	0.087**	-0.015	0.037	0.073**	0.079***	0.005
	(0.036)	(0.028)	(0.044)	(0.034)	(0.027)	(0.003)
Observations	1,439	2,881	2,881	2,881	2,881	2,881
Control mean	0.770	0.730	0.400	0.170	0.110	0.000

Notes: This table presents the results of the regression on the depth of floodwaters reported by the households in the outcome surveys on a dummy which classifies villages into high and low-flooded based on the variation in rainfall received in 2022 from the historical rainfall. Water enter is a dummy equal to 1 if the household reported that water entered the house. *Water_20* is a dummy equal to 1 if the household reported that water entered up to 20% of the walls. *Water_40* is a dummy equal to 1 if the household reported that water entered above 40% of the walls and so on. The sample is restricted to the Matiari district, where the outcome surveys were conducted. Standard errors are clustered at the village level." ***=significant at 1%, **=significant at 5%; *=significant at 10%

Table A3: Attrition rates by Union council

	Attrition
Abdul Wahid Burio	1.28
Nobat Mari	2.63
Sher Muhammad Thorha @ Khyber	7.35
Tajpur	9.00
Karam Khan Nizamani	7.34
Matiari	64.77
Bhit Shah	3.53
Fateh Muhammad Shah Ajnani@Saeed Khan Laghari	4.94
Shahmir Rahu	0.93
Sekhat	5.83
Palijani	1.37
Ajan Shah	9.85
Muhammad Ramzan Uner	0.00
Oderolal Village	6.00
Bau Khan Pathan	9.85
Faqeerabad	2.00
Shah Pur at Arif Khatian	3.85
Muhammad Hussain Hingoro	2.22
Oderolal Station	9.46
Zair Pir	3.61
Bhanoth	4.80
Bhali Dino Kaka	0.92
Sikanderabad	1.16
Khando	2.25
Makhdooman- Joon -Landhiyon	6.78
Baudero	4.35
Faqir Nooh Hothyani	2.92
Shah Alam Shah Ji Wasi	0.00
Old Saeedabad	5.31
Jiandal Kot	4.17

Notes: This table reports the attrition rates for each of the Union council where we conducted the outcome surveys.

Table A4: Attrited versus non-attrited

	Non-attrited	Attrited	Diff	p-val
Poverty score	23.01	22.55	-0.45	0.02
Livestock				
Own livestock	0.45	0.46	0.01	0.85
Livestock Num	1.66	1.54	-0.13	0.44
Non- livestock Assets				
Mobile	0.76	0.73	-0.03	0.06
Own Motorcycle	0.08	0.08	-0.00	0.98
Own Cooking stove	0.16	0.19	0.02	0.39
TV	0.14	0.10	-0.04	0.00
Own house	0.62	0.49	-0.13	0.00
Rooms	1.33	1.24	-0.09	0.01
Flood Damages				
House Damaged	0.79	0.82	0.04	0.02
Livestock died	0.17	0.16	-0.01	0.53
Relocated	0.36	0.37	0.02	0.54

Notes: This table reports the characteristics of the attrited and non-attrited in the followup survey.

Table A5: Livestock before floods

	Sheep(=1)	Goat(=1)	Cow(=1)	Bullock(=1)	Buffalo(=1)	Chicken(=1)
	(1)	(2)	(3)	(4)	(5)	(6)
Loan RD	-0.000	0.065**	0.019	0.007	-0.008	0.001
	(0.002)	(0.031)	(0.017)	(0.007)	(0.030)	(0.009)
Observations	3,320	3,320	3,320	3,320	3,320	3,320
Control mean	0.000	0.310	0.060	0.010	0.210	0.020

Notes: This table reports the impact of access to loans on different types of livestock before the floods. Bandwidth is restricted to +/- 4. Standard errors are clustered at the village level. ***=significant at 1%, **=significant at 5%; *=significant at 10%

Table A6: Housing quality

	Concrete roof(=1)	Concrete Floor(=1)	Rooms	Toilet
	(1)	(2)	(3)	(4)
Loan RD	-0.049**	-0.046**	-0.067**	-0.053***
	(0.024)	(0.021)	(0.030)	(0.019)
Observations	5,324	5,477	5,565	6,002
Control mean	0.540	0.240	1.350	0.690

Notes: This table reports the impact of access to loans on individual components of the housing quality index. Bandwidth is restricted to +/- 4. Standard errors are clustered at the village level. ***=significant at 1%, **=significant at 5%; *=significant at 10%

D Appendix - PSC construction

Indicator	Select one option				Score
How many people in the household are under the age of 18 or over the age of 65?	0-2 (15)	3-4 (10)	5-6 (5)	7+ (0)	
What is the highest educational level of the head of the household (completed)?	0 (0)	1-5 (1)	6-10 (3)	11+ (10)	
How many children in the household between 5 and 16 years old are currently attending school??	No children (4)	All attending school (4)	Some attending school (3)	None attending school (0)	
How many rooms per person does the household own?	≥ 0-≤ 0.2 (0)	> 0.2-≤ 0.3 (2)	>0.3-≤ 0.4 (4)	>0.4 (12)	
What kind of toilet is used by the household?	Flush connected (3)	Dry raised laterine (2)		No toilet (0)	
Does the household own at least one refrigerator freezer or washing machine?		Yes (3)	No (0)		
Does the household own at least one air conditioner air cooler, geyser or heater?		Yes (9)	No (0)		
Does the household own at least one cooking stove cooking range or microwave oven?		Yes (5)	No (0)		
Does the household own at east one TV?		Yes (2)	No (0)		
Does the household own the following engine driven vehicles?	Car/tractor (24)	Motorcycle (7)		None (12)	
Does the household own the following livestock?	buffalo/bullock (6)	Cow/goat (2)		None (0)	
How much land does the household own?	0 (0)	>0-≤ 12.5 (4)		>12.5 (7)	

E Appendix - SUCCESS program

SUCCESS program has tow main components: social mobilization and support package. The social mobilization strategy forges a development of partnership between the rural communities and the Rural Support Programs (RSPs). The objective of RSPs is to help communities form the community, village, and union council-level organizations represented by female members of households.

Community organizations - The basic form of these local organizations was at the neighborhood level, which are called Community Organizations (CO). All households in the treatment area living in that neighborhood were eligible for membership in the CO. A typical CO has 15-20 members. To run day-to-day affairs, each CO elected a president and manager who were then trained by the RSPs. No pre-specified duties of COs were required. Every CO was free to set its mission and objectives. Members of the CO would meet once a month. In every meeting, community resource persons (women) trained by RSPs with sector-specific knowledge conducted awareness sessions on a range of topics, such as education, family planning, nutrition, health, and civic rights to communities.

The RSP social mobilization teams worked with the COs to encourage its members to prepare their micro-investment plan (MIP), which lies at the core of the approach to household poverty reduction. Every CO member identified an income-generating opportunity that she could manage with the help of her household members, through which she believed she could increase household income if facilitated with a small grant, interest-free loan, or training. She decided on the MIP in consultation with her household, other CO members, and RSP field staff.

Village organizations - Community organizations subsequently federated into village organizations (VO). VOs were formed by considering the geographical proximity and access between different settlements where women could easily attend monthly VO meetings. Each CO in the respective VO area nominated up to two members to represent the CO in the VO. These members form the VO general body. The VO general body members elected a president and manager amongst its members to run the VO's day-to-day affairs. The key function of a VO is to ensure maximum coverage of households into COs and provide supportive supervision to its member COs in identifying program beneficiaries, planning, and implementing village-level development activities. The RSPs social mobilization teams worked with each VO to prepare a Village Development Plan (VDP). Notably, the VOs were provided with a grant to implement a village-level community infrastructure project in the VO catchment area and provided funds to implement the income-generating grants component of the program. The VOs also engaged in running school enrolment campaigns and immunization campaigns at the village level.

Local support organizations - Village organizations subsequently federated into union council-level local support organizations (LSO). Each VO nominated up to two of its members to represent the VO in the LSO. These members form the LSO general body. The LSO general body members elected an Executive Committee among its members to run the LSO's day-to-day affairs. The Executive Body included one chairperson/president, one General Secretary, one treasurer as office-bearers, and two other members. The key function of the LSO is coordination and implementation of development activities at the UC level, formation of linkages with government service departments and other development organizations, and providing guidance and support to VOs and COs. The LSO was also granted a revolving fund called the Community Investment Fund (CIF). The LSO uses this capital grant to extend small loans to poor (PSC 0-23) households. Loans are extended through COs, and the management of the CIF is entrusted to the members of the LSOs. The RSPs provided technical support and training to help community institutions manage the CIF as long-term revolving funds. The CIF serves two broad objectives: (a) to ensure the sustainability of LSOs and (b) to help poor members increase their incomes by setting up and enhancing existing small businesses and creating livelihood assets (e.g., investment in livestock and agriculture inputs) through CIF loans.

Support packages .

After the formation of the community institutions, every CO member prepared a Micro Investment Plan (MIP) to increase their household income. The SUCCESS program provided support to CO members to implement their MIPs from the following set of support packages

Community Investment Fund (CIF) - CIF is a capital grant from the SUCCESS program to community institutions at the LSO level. The main purpose of the CIF was to support the financial and institutional sustainability of community institutions and to provide financial access to CO members. The LSOs managed the CIF as a revolving fund while offering micro-loans to women from poor households to start income-generating activities or build productive assets. To access CIF loans, a woman must be a member of the CO, must be poor (PSC 0-23), and must agree to pay back the CIF according to the terms and conditions set by the LSO.

Income Generating Grant (IGG) - The objective of IGG was to support the poorest female community members through a one-time cash grant to start income-generating activities. The IGG was managed by VOs and was provided to only the poorest CO members

(PSC 0-9).

Micro Health Insurance (MHI) - RSPs contracted private insurance company to provide MHI. There was no user fee attached to the MIP, and the RSPs provided a premium of Rs. 1000 per family per year to the insurance company. Medical services were provided by private hospitals selected by the insurance company. The RSPs provided awareness sessions among community members about the benefits and use of the insurance and enrolled beneficiaries for the insurance scheme in consultation with community institutions. All poor CO members with a poverty score of 0-12 were eligible for the MHI. If the insurance holder was married, the beneficiaries would include herself, her husband, all children under 18 years, parents-in-law, and sister-in-law under the age of 18 years. If she was single, the household beneficiaries included her parents and siblings under the age of 18.

The benefit package included only inpatient services, which consisted of hospital admission for a minimum of 24 hours, support for both normal and surgical deliveries, coverage for doctor fees, medications, laboratory tests, and surgeries up to a total of Rs. 25,000 for each eligible beneficiary. Additionally, the scheme provided a transport allowance for hospital visits and a one-time cash payment in the event of the insurance holder's death, complete or partial blindness. In cases of emergency treatment, expenses of up to Rs. 25,000 were eligible for reimbursement incurred at any hospital.

Technical and Vocational Skills Training (TVST) - The TVST was offered to young women and men from the CO member poor households (PSC 0-23). Men opted for car driving and motorcycle repairing training while the women opted for handicraft, embroidery and livestock farming. The TVST training duration varied from two weeks to 2 months depending on the trade of the TVST. The TVST was delivered by the Institute of Rural Management (IRM).

Community Physical Infrastructure (CPI) - To improve the basic community-level infrastructure and productive assets, VOs were provided with grants for building the CPI. The VO members identified, oversaw, and maintained the CPI projects. The RSP assisted the VOs in conducting needs assessments, facilitating VO members to identify infrastructure needs and prioritize them. Once a consensus is reached on a specific need, VO members pass resolution-seeking technical and financial assistance from the RSP. The community contributes to the cost of the project, typically in the form of land, labor, and local materials. Prioritized needs are included in the village development plan created by the VO. Upon receiving a resolution from a VO, the RSP formed a team consisting of an engineer and social organizer. This team conducted a feasibility survey of the proposed scheme, covering technical (design, drawings, and environmental aspects) and social aspects (looking for access to the majority of the community, social costs and benefits, and any potential conflicts), and prepared cost estimates. Once the feasibility study is approved, the VO established three committees: a project implementation committee, project audit committee, and project maintenance committee. These committees were accountable to the member COs. Once the CPI project is completed, maintenance of the project is the responsibility of the VO.