Adapting to Thrive: Training and Access to Finance to Reduce Climate Vulnerability Among Smallholder Farmers in Nepal*

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Abstract

Climate change poses significant threats to agricultural production, particularly for smallholder farmers who often lack the resources to cope with adverse weather events. This study examines the impacts of a multifaceted intervention consisting of training and financial support to promote the adoption of climate adaptation practices and improve livelihoods among smallholder farmers in Nepal. We use an exogenous variation in project roll-out resulting from the 2015 Nepal administrative restructuring for causal effect identification. Results show that the intervention leads to increases in certain climate adaptation practices, income, and resilience. These increases are primarily driven by improved access to information, enhanced social capital, increased production, and greater output market participation. Findings highlight the critical role of climate adaptation interventions in improving the livelihoods of climate-vulnerable smallholder farmers.

Keywords: Climate change, adaptation practices, resilience, smallholder farmers, Nepal
JEL codes: Q54, Q12, O12

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1 Introduction

Climate change in the form of extreme temperatures and varying rainfall patterns could reduce crop yield by about 17%, resulting in an annual economic loss equivalent to 0.3% of the global gross domestic product (Stevanović et al., 2016; Nelson et al., 2014). Smallholder farmers are the most vulnerable group to climate change due to their geographical position and limited financial, human, and physical resources (Morton, 2007).[1] On the flip side, agriculture, forestry, and land use changes collectively contribute about 25% of global greenhouse gas emissions—a major driver of climate change (World Bank, 2022a). The interconnected relationship between agriculture and climate change underscores the need for production practices that enhance smallholder farmers' adaptive capacity (i.e., adaptation practices) while potentially also mitigating emissions as co-benefits for sustainable agriculture and food systems (World Bank, 2023).

Despite the noble goals of improving productivity and reducing emissions simultaneously, the uptake of climate adaptation practices remains low. On the supply side, promoting the adoption of climate adaptation practices is challenging as they require context-specificity and cost-effectiveness (Eriksen et al., 2021; Arslan et al., 2015). On the demand side, resource constraints (e.g., information, monetary, and technology), investment risk, and inadequate awareness of climate risks may limit their adoption (Emerick et al., 2016; Rosenzweig and Udry, 2020; Dercon and Christiaensen, 2011). Furthermore, unlike adopting new seeds, farming techniques, or machinery– a topic well covered in the literature on the economics of adoption– climate adaptation practices involve how individuals or communities perceive and deal with environmental changes (Zilberman et al., 2012). Notably, what distinguishes climate adaptation practices from typical technology adoption (e.g., using organic fertilizer or employing soil fertility improvement techniques) is that in some cases, they may not yield immediate observable benefits for farmers (McCarthy et al., 2011).

We examine whether bundling training with financial support increases the adoption of climate adaptation practices and improves the livelihood of smallholder farmers. The multifaceted intervention was implemented in Karnali and Lumbini Provinces of Nepal from 2016 to 2022 by the Ministry of Forest and Environment (ND-GAIN, 2023; Eriksen et al., 2021). The project activities consist of training for lead farmers and field staff, who subsequently deliver training and technical assistance to other farmers in their communities. The project complements training with financing for either (1) a production scheme such as agricultural, afforestation, and livestock ac-

[1] The repercussions of reduced production can extend beyond economic concerns for smallholder farmers, potentially making them susceptible to being caught in poverty traps and affected by civil conflicts and forced displacements given their limited ability to recover from shocks (Cohn et al., 2017).

tivities for individual farmers (financing scheme one), or (2) an infrastructure scheme such as building climate-resilient infrastructure such as irrigation canals, rainwater recharge systems, or landslide control structures for communities (financing scheme two). Both financing schemes had equivalent values, with farmers contributing 20% of the total cost and the remaining covered by the project.

The training component of the intervention is likely to reduce information asymmetry among smallholder farmers through information and capacity-building activities provided by lead farmers and observation of practices within groups or communities (Kondylis et al., 2017; Beaman et al., 2021; Fafchamps et al., 2020). Co-financing complements the training component by availing the new technology or inputs, which may otherwise be financially out of reach for many farmers, thereby addressing monetary constraints hindering investment in agricultural technologies (Jew et al., 2020; Macours, 2019). The requirement for farmers to contribute 20% of the investment cost in the form of in-kind labor can foster ownership and ensure the long-term sustainability of the investments. The co-financed nature of the investment may also alleviate risk constraints faced by farmers (Omotilewa et al., 2019; Fishman et al., 2022). Overall, the additional support in production technology has the potential to intensify farming practices and increase earnings, thereby enhancing smallholder farmers' capacity to withstand future climatic and non-climatic shocks. Furthermore, certain climate adaptation practices promoted by the project (e.g., irrigation systems, erosion control structures) may enable households to save time otherwise spent fetching water or building traditional erosion control measures. As a result, households can allocate more time to farming and non-farm income-generating activities or participate in the market, which can enhance their livelihoods.

Our identification strategy to estimate the project's impact relies on leveraging exogenous variation in project roll-out resulting from the nationwide administrative restructuring between 2016 and 2017.[2] Before the nationwide restructuring process was implemented, the project team identified some project areas and households and conducted a baseline survey covering 1,326 households from 28 Village Development Committees (VDCs).[3] The baseline survey was conducted without anticipation of the subsequent project halt until 2018, prompted by the administrative restructuring. The restructuring abolished the VDC system and reconfigured the 28 VDCs covered by the baseline survey into 43 wards. After the restructuring concluded, project activi-

[2]Nepal adopted a new Constitution in 2015 as a federation of seven provinces, each with a chief minister and local legislature that elects the local government. Previously, the country was in a unitary government system. As part of this new constitution, the administrative restructuring occurred from 2016 to 2017. See Agergaard et al. (2022) for a detailed description of the restructuring process and background history.

[3]A Village Development Committee (VDC) was the local-level administrative unit in Nepal before the administrative restructuring. After the restructuring, the VDC system was abolished.

ties resumed in 2018. However, the project could be implemented in 32 wards in the baseline survey (998 households). The remaining 11 wards in the baseline survey (328 households) were dropped off as they fell outside the project command area. The administrative restructuring led to these 11 wards being incorporated into separate municipalities or areas, where project running costs and time requirements associated with establishing relationships with new local government bodies could have been substantially higher. Since these wards (households) did not receive intervention as initially planned, we use them as control wards (households) in this study. The other 32 wards (998 households) received intervention as planned before the administrative restructuring and are used as treatment households (wards).

We link baseline and endline data and primarily use the analysis of covariance (ANCOVA) regression to estimate the intent-to-treat effects of the project. First, we find that the project significantly increases the adoption of selected climate adaptation practices among treatment households compared to control households. The standardized index of climate adaptation increased by 0.14 standard deviations. Impacts are more pronounced on practices that are likely to bring immediate benefits, such as soil erosion control structures (e.g., terrace, gabion, and drainage) or livestock stall feeding, compared to practices that may not yield immediate boosts in production, such as soil fertility improvement practices (e.g., use of biochar, mulching, and crop compost). This may be driven by the uncertainty of benefits from adopting some of these practices or the myopic nature of individuals' behavior in recognizing future benefits (Arbuckle Jr et al., 2015). Second, we find positive impacts on livelihood outcomes such as household income (23%). The project also boosted household capacity to withstand future shocks as measured by resilience. Depending on the alternative indicators, we find that the resilience level of treatment households is 16% to 39% higher compared to control households.

We examine two sets of mechanism variables to explain the results related to primary outcome indicators. The first set consists of intermediate outcomes, including access and use of training services, social capital through membership in different economic and social groups, and credit access (Arulingam et al., 2022; VoxDev, 2019; Bandiera and Rasul, 2006). Results show that the project significantly increases training services and their utilization among treatment households. Additionally, the project enhances participation in economic and social groups for both men and women. However, the amount of loans was smaller for treatment households than control households, suggesting a substitution between project funds and those from other sources. The second set of mechanisms includes revenue from production, climate shock-driven harvest losses and asset losses, and output market participation (Kafle et al., 2022; Hossain et al., 2023). We find that the project increases revenue from farm activities, reduces asset loss, and increases market participation for the treatment households.

We complement the main results with additional analyses. Previous studies show that the low adoption of climate adaptation practices can be due to resource constraints or insufficient awareness about climate shifts (Arslan et al., 2015; Emerick et al., 2016; Michler et al., 2019). Therefore, we examine how the project impact estimates differ depending on the intensity of climatic shocks. We measure the deviation in climate conditions from its long-term pattern, namely the variation in growing degree days (GDD), rainfall, and temperature levels. We find that the adoption of climate adaptation practices is significantly higher when we account for the variation in GDD and temperature indicators. This finding indicates that households are more likely to adopt such practices in response to climate shocks and when resources are available. The former aligns with existing evidence that households adjust their farming practices (i.e., choice of inputs) in the presence of climate shocks (Alam et al., 2017; Aragón et al., 2021; Jagnani et al., 2021).

The bundled nature of the project (training and co-finance) presents challenges in separating the impact of individual components of the project. Existing literature documents that information or training-related interventions are effective when complemented with other inputs such as credit and insurance (JPAL, 2018; VoxDev, 2019). This may suggest that the co-finance part of our intervention drives the bulk of the impacts. Assuming that the impact of training is homogeneous among treatment households, we explore which financing scheme (i.e., production scheme or infrastructure scheme) generates a greater impact on treatment households. To do so, we measure the distance between project-financed infrastructure and household locations and provide suggestive evidence that the project impact is higher among households who benefited from the production schemes than those who benefited from the infrastructure scheme.

The findings of this study align with those in the literature on the impact of multifaceted interventions aimed at promoting climate adaptation practices. Several studies demonstrate the positive impacts of such interventions, such as insurance, credit, cash transfers, training, and climate-resilient crop varieties, to mitigate the adverse impacts of climate shocks (Lane, 2022; Macours et al., 2022; Pople et al., 2021; Emerick et al., 2016; Karlan et al., 2014). Our findings complement this literature by showing the positive impact of training and co-finance intervention to promote the adoption of climate adaptation practices. We show that input support and training contribute to increased production, assets, and income, thereby bolstering resilience against future shocks (Dhakal et al., 2022; Huang et al., 2015).

Our study makes several contributions to the literature. While much of the existing literature has focused on the economics of adoption by examining the uptake of new seeds or farming techniques (Ruzzante et al., 2021; Beaman et al., 2021; Fafchamps et al., 2020; Bandiera and Rasul, 2006), our study focuses on the adoption of climate adaptation practices where individuals respond to major environmental changes (Zilberman et al., 2012). By investigating how farmers respond when climate adaptation practices may not generate immediate benefits, our study contributes to the understanding of behavioral responses to evolving climate dynamics. We show that treatment households are more likely to adopt practices that can show immediate benefits (i.e., soil erosion control structures) than practices that may not show immediate benefits (i.e., soil fertility improvement techniques). Furthermore, we quantify the impact of exposure to climate change (e.g., extreme temperature) on adoption and show that those exposed to high variation in extreme temperatures are more inclined to adopt.

Our study also complements the research on the dual objective of promoting climate adaptation practices while improving livelihoods. Existing studies focus on the impacts of individual factors driving the adoption of new farming technologies (VoxDev, 2019; Hemming et al., 2018). Our study takes a slightly different angle. We show that a multifaceted intervention combining access to training services with cofinancing leads to increased adoption of climate adaptation practices, enhanced social capital, and increased earnings. These factors contribute to better livelihood outcomes. Unlike most impact evaluation studies, which assume full certainty in livelihood outcomes (Cissé and Barrett, 2018; Phadera et al., 2019), we also focus on households' capacity to withstand future shocks. We show that the multifaceted intervention has positive effects on smallholder farmers' livelihoods and strengthens their resilience to future shocks.

The remaining section of the paper is as follows. We discuss the background and intervention in Section 2. Section 3 describes the study design and data, and Section 4 discusses the empirical strategy. We present the main results in Section 5, followed by Section 6 on the mechanisms. Section 7 presents additional results. We conclude in Section 8.

2 Background and Program Description

2.1 Context: Exposure to Shocks and Adaptation Practices in Nepal

Smallholder farmers use about 76% of Nepal's cultivated land primarily through subsistence crops or crop-livestock mixed farming systems (CIAT, 2017). Remarkably, these farms contribute about 70% of the nation's food production (Rapsomanikis, 2015). However, they face recurrent climate and non-climate shocks, undermining their agricultural production, income, and livelihoods (Bandara and Cai, 2014; Alinovi et al., 2010). Appendix Figure A.1 shows four major types of natural disasters that took place in Nepal over time. Estimates suggest that climate variability and extreme events cost the country between USD 270 and 360 million, which is about 1.5% to 2% of the country's GDP (CIAT, 2017). Another recent study shows that the combined impacts of heatwaves, floods, and agricultural productivity shocks could amount to a 7% loss in GDP by 2050 compared to scenarios without damage (World Bank, 2022b). These adverse climatic conditions have significant implications for household well-being. In the short term, they may worsen agricultural production, income, and overall vulnerability (Bandara and Cai, 2014; Alinovi et al., 2010). In the longer run, households may be compelled to migrate from their villages (Arslan et al., 2021; Nepal et al., 2021; The New York Times, 2020; Cai et al., 2016).

The Government of Nepal introduced the National Climate Change Policy to address the challenges related to climate shocks in 2011 (Paudel et al., 2017). The Government also enhanced the nationally determined contribution (NDC) under the Paris Agreement to reduce long-term low greenhouse gas emission development strategy. It implemented the National Adaptation Programme of Action (NAPA) in 2015. Under the NAPA framework, the Local Adaptation Plans of Action (LAPA) were established to support vulnerable populations at the community level. The LAPA framework identifies context-specific adaptation measures and mobilizes necessary resources and service delivery agents for the government to farmers via local administrations. Despite the efforts made by the government, the adoption of climate adaptation practices is generally low or moderate (CIAT, 2017). Most adaptation strategies rely on local knowledge and are linked to disaster risk management and diversification (Rijal et al., 2022). Like those in other developing countries, multiple ex-post coping mechanisms are used to mitigate the impacts of shocks, including asset sales, utilization of savings, borrowing money, seeking assistance from social networks, and reducing consumption to safeguard assets (Alinovi et al., 2010; Heltberg and Lund, 2009; Kazianga and Udry, 2006).

2.2 The Intervention: the ASHA Project

The ASHA project was launched in 2015 and implemented from 2018 to 2022 by the Ministry of Forests and Environment (IFAD, 2014). The project covered seven mid-western districts in Nepal: Dailekh, Kalikot, Salyan, East Rukum, West Rukum, Jajarkot, and Rolpa. The geographical coverage is shown in Appendix Figure A.2. The project aimed to bolster adaptive capacities among vulnerable smallholder farmers engaged in crop, livestock, or forest activities. The project integrated information and training with co-financial support for infrastructure development or production practices.

2.2.1 Information and Training

The project conducted a comprehensive four-week training program for 429 lead farmers, 107 mid-level technicians, and six field resource persons through farmer field schools. Trained individuals subsequently disseminated knowledge to farmers in their communities. Households also received personalized consultancy from lead farmers for nominal fees. The training covered multiple topics, including (1) soil erosion, soil fertility, and soil moisture conservation, (2) home gardening, (3) using cow urine as pesticides and farmyard manure, (5) livestock shed management, and (6) rotational grazing techniques.

2.2.2 Co-finance

The project provided co-financing in two schemes: (1) infrastructures for farmer groups and (2) crop farming, afforestation, or livestock production support. For both schemes, the project covered 80% of the cost, and smallholder farmers contributed the remaining 20% in-kind (i.e., through labor supply).

1. **Co-finance for infrastructure**: This scheme covered the construction and upgrade of infrastructures such as irrigation canals and ponds, rainwater recharge systems, multi-use water supply pipes, renewable energy technologies, and erosion control structures. The project formed a sub-committee for each farmer group responsible for maintaining the infrastructure. The committee is responsible for collecting user fees from members to cover maintenance costs.

2. **Co-finance in production activities**: The project financed production activities. This scheme covered the cost of labor-efficient farming equipment for commercial vegetable farming and fruit cultivation. The project co-financed livestock shed improvement, stall feeding, and forage and fodder management for households rearing livestock. The project also covered nursery establishment and seedling support to promote afforestation activities in forest and private lands.

All households received information and training, but co-finance was available for either infrastructure or production activities. Thus, we define two treatment groups: (1) training plus infrastructure group and (2) training plus production support group. By completion, the project benefited around 118,595 households in 200 wards. Approximately 55% receiving infrastructure support. The project cost per household was roughly the same for both groups, around USD 220 per household.[4]

The project used specific criteria for household selection. Following the announcement of the project roll-out in a ward, interested farmers and groups submitted applications outlining their required support. Priority was given to households affiliated with farmer groups or associations owning less than 0.05 hectares of land and not

[4] A recent study shows that the cost of rice production per hectare is about USD 680.

receiving benefits from other government/NGOs concurrently. After field verification, an orientation program initiated the subsequent stages of project implementation.

3 Study Design and Data

3.1 Design

The study design is based on two considerations: (1) a baseline survey conducted by the project team in 2016 and (2) the national-level administrative restructuring between 2016 and 2017. The ASHA project team conducted a baseline survey of 1,326 households from 28 VDCs in 2016. The project team identified all these households as potential beneficiaries, and the baseline data was collected for monitoring purposes (i.e., to compare the pre-intervention and post-intervention outcomes of the beneficiaries).

After the baseline survey, a national-level administrative restructuring process began in Nepal, abolishing the VDC system. This restructuring led to the establishment of 753 municipalities nationwide, which were further divided into 6,743 wards. As a result, the 28 VDCs in the baseline survey became 22 municipalities and 43 wards. The restructuring process paused the project's activities between 2016 and 2017. The project activities commenced in early 2018. Appendix Figure A.3 depicts the timeline of this study. The administrative restructuring and associated delays and changes in local administration caused a substantial change in the program's ability to implement the project for these baseline households. The project team could not implement activities in 11 out of the 60 baseline wards, as they fall outside their command area and are governed by separate local authorities. The remaining 32 out of the 60 baseline wards received the project activities as planned.

We consider these 32 baseline wards where the ASHA project was implemented as previously planned as the treatment wards, while the 11 wards where the project could not be implemented as they fell out of the project areas are considered as control wards. Appendix Figure A.2 shows the treatment, control, and full study locations. The control words are mostly located in municipalities where the project had no activities. In some cases, there is geographical continuity between control and program wards; the decision to exclude these control wards was driven by the high administrative costs of implementing the intervention and the challenges associated with establishing relationships with new local government bodies. Within these 43 wards, the total number of baseline households is 1,326, with 998 from treatment wards and 328 from control wards. Appendix Figure A.4 presents the sampling details in a flowchart, and Appendix Table A.1 shows the sample distribution by district and treatment status.

3.2 Data

We conduct the endline survey between December 2022 and February 2023 to follow up with the 1,326 baseline households. We successfully collected endline data from 1,108 households, achieving an 84% success rate. The success rate was 84% in the treatment and 82% in the control groups. Appendix Table A.1 shows the final sample size. The primary reason for unsuccessful surveys is that enumerators could not locate those households. The baseline line survey did not collect phone numbers or alternative identification of the households. Considering the time lapse of 6 years since the baseline survey, it was expected to attrition rate would be higher. We check whether the attrition rate systematically relates to households' treatment status and find that the attrition rate is not systemic to households' treatment status (Appendix Table A.2).

We collect extensive data on household members and their demographic characteristics, access to basic services (e.g., water, sanitation, electricity), asset holdings, economic activities, and income for the last production cycle (October 2021 to September 2022) during the endline survey. We also gather data on households' access to different benefits and finance. The baseline survey, conducted by the project team in 2016, collected similar data on demographics, basic services, and asset holdings. The baseline survey used different instruments for data collection, especially for key indicators like income and production. For instance, the baseline line survey collected income information by asking the respondent about the total yearly income from farming, business, or wages, whereas the endline survey used a detailed questionnaire to collect activity-wise income data. The former makes the baseline and endline data for income, production, and credit access not comparable. As discussed in later sections, we rely on endline data for impact estimates while using the information in the baseline survey to control for initial conditions.

3.3 Outcome Variables

The first set of outcome variables focuses on climate adaptation practices related to farming and livestock activities. Appendix Table B.1 provides a detailed description of each indicator. Previous studies suggest that extension and training programs often fail to achieve their intended impact due to limited relevance to the target audiences. Designing intervention without consulting local stakeholders, overlooking the social, economic, and cultural context of participants, and lacking complementary inputs are primary reasons for low adoption (Takahashi et al., 2020; Chavas and Nauges, 2020; Magruder, 2018; Arslan et al., 2014; Koundouri et al., 2006). This project addressed both contextual and complementary input issues by promoting climate adaptation practices that are context-specific and complemented with co-financing schemes.

The second set of outcome variables includes income and asset ownership.

Despite considerable efforts to build resilience through development projects, most studies evaluate the impacts of development projects on income or assets assuming full certainty. We go beyond this assumption by considering indicators of resilience that distinguish between transient welfare boosts and structural changes affecting future economic circumstances (Phadera et al., 2019). We use complementary indicators of resilience, which refer to the household's capacity to withstand and recover from shocks. Resilience is not directly observable and can be measured using various methods (Jones and d'Errico, 2019; Upton et al., 2022; Cissé and Barrett, 2018). We use the three commonly used resilience measures. The first measure is the Resilience Indicators for Measurement and Analysis II (RIMA), which calculates the resilience capacity index by considering four key pillars: access to basic services, assets, social safety nets, and adaptive capacity (FAO, 2023). The second measure is an indicator proposed by Cissé and Barrett (2018) (hereafter, CB), which estimates the probability of a household reaching or surpassing a predetermined normative benchmark level using regression analysis. Third, we use a subjective indicator of resilience based on the aggregate score of self-reported questions (Jones and d'Errico, 2019). Appendix B details all three indicators' definitions, measurement steps, and comparability.

3.4 Baseline Balance

Appendix Table A.3 shows the statistical balance pre-intervention balance of treatment and control households. Given that the administrative restructuring was outside the influence of the households, one would expect statistical balance in baseline characteristics between treatment and control groups. We find that they are mostly balanced, except for the sex of the household head, livestock income, and household assets. Regarding access to various infrastructures (e.g., electricity, water, sanitation, and dwelling characteristics), we do not find any significant differences. The control households had higher average livestock income and more household assets than the treatment households. Only three of the 25 indicators show imbalances at a five or less significance level.

Given the absence of additional pre-program survey rounds, it remains unclear whether the baseline imbalances in those three cases are incidental or indicative of consistent differences between the treatment and control groups. Following Gibson and McKenzie (2014) and Crump et al. (2009), we adopt a matching approach to address this issue. We match each treatment household with the five nearest control households (i.e., neighbors) and exclude 31 treatment households from the analysis whose estimated propensity scores fall outside the range of the control households' maximum and minimum propensity scores.[5] The trimmed sample shows an improve-

[5]We deviate slightly from Crump et al. (2009)'s suggestion of dropping households with propensity scores outside the 0.1 to 0.9 range. We observations with propensity scores above 0.95.

ment in the balance between the treatment and control groups, as shown in Table 1, with only livestock income remaining statistically different. We use this sample in all subsequent analyses.

As previously mentioned, treatment and control households were selected for treatment before the administrative restructuring, but 11 wards fell outside the project areas after the restructuring process was completed. The restructuring turned the households from those 11 wards into control households. Appendix Figure A.2 shows that treatment and control wards are adjacent and are only separated because they belong to separate municipalities. We examine ward-level indicators such as road density, land area, distance to the nearest city, and elevation. Treatment and control wards are statistically balanced. Appendix Figure A.5 shows the average temperature and rainfall in treatment and control wards over time. We find a similar trend over time for all these indicators in treatment and control wards. Similar ward-level characteristics reinforce the internal validity of our study.

3.5 Descriptive Statistics

Appendix Table A.5 presents an overview of the sample's demographic characteristics, infrastructure access, asset holdings, and income-related variables based on endline data. The average household size is 4.20, with an approximately equal number of men and women. The household size in this study aligns with the average household size in rural Nepal, which was about 4.70 in 2016-2017 (CBS Nepal, 2016). About 35% of the households are headed by women, significantly higher than the rural Nepal average of 22%. The average age of household heads is around 50 years, and most have attained education up to the primary level (76%). About 82% of the households have access to electricity, while 67% have access to drinking water from pipelines or protected wells. Moreover, around 80% of the sample resides in dwellings with concrete walls, although only 18% reported having concrete roofs. Crop farming contributes to about half of household income.

4 Estimation Framework

We exploit the fact that the project did not roll out as initially planned in a few wards, resulting from administrative restructuring, as a natural experiment to establish an exogenous variation in treatment allocation. We consider the wards where the baseline survey was conducted and ended up being covered by the project as treatment wards. Control wards are those in the baseline survey where project implementation had been planned, but the project was not implemented due to administrative restructuring. Our key assumption is that the assignment of the control wards due to the administrative restructuring was beyond the control of households in those wards and project staff. We primarily use the ANCOVA regression to estimate the treatment effect as follows:

$$Y_{iwt} = \beta_0 + \beta_1 \times \mathrm{T}_w + \beta_2 \times Y_{iw,t-1} + \mu X_{iw,t-1} + \eta \mathrm{V} + \zeta_{iwt}, \tag{1}$$

where Y_{iwt} is the outcome variable y of household i from ward w in time t; T_w is an indicator variable taking a value of 1 if the household i is from ward w, indicating that the household is a treatment household and 0 otherwise. We control the baseline $Y_{iw,t-1}$ value for outcome variables with baseline data available. $X_{iw,t-1}$ presents household-level baseline control variables (e.g., household size, number of male members, whether headed by a female, age of household head, access to electricity, safe drinking water, sanitary latrine, dwelling characteristics), and V are fixed effects at VDC level. VDCs no longer exist in the current administrative system. However, it was the administrative reference when project staff decided on the program roll-out and baseline survey. Finally, ζ_{hwt} captures household-level unobservable factors. We cluster the standard errors at the ward level, as the project was implemented at the ward level eventually.[6]

Our identification strategy is supported by the fact that household and ward selection was completed before the administrative restructuring. Project activities were not rolled out during the restructuring period and commenced after completion. The former implies that selection into treatment and control groups is as good as random. Treatment and control households are similar regarding both observable and unobservable characteristics. While we show that the baseline characteristics are balanced between treatment and control groups (wards) in the previous section, we fine-tune the baseline balance further by dropping more households based on their baseline propensity scores (Crump et al., 2009). Thus, the treatment and control households are comparable in observable and unobservable characteristics.

We use the ANCOVA method over the difference-in-difference method for two reasons. Firstly, baseline data were collected in 2016, whereas the project activities started in 2018 and thus may not truly reflect the baseline period. Secondly, the survey questionnaire used for the baseline survey was not directly the same as the one used in the endline survey, which complicates the direct comparison of income or asset indicators between the two survey rounds. Thus, we include these baseline variables as controls to improve the precision of our estimates.[7]

[6]We did not employ clustering at the VDC level, as the VDC no longer exists in the Nepalese administrative system. To address geographical and development heterogeneity, we include VDC-level fixed effects in each regression. Nevertheless, our analysis did not reveal any significant differences in the precision of impact estimates when clustering at the VDC.

[7]A related discussion on the use of ANCOVA regression in cases where measurement changes between baseline and follow-up data are available in the World Bank blog.

The coefficient of interest, β_1, represents the intention-to-treat (ITT) effect. The project's impact on the treated households is based on their initial assignment to treatment. Not all baseline treatment households ultimately received project benefits for various reasons, such as project interruptions or incomplete coverage. According to the project's administrative records, approximately 87% of the treatment households received at least some benefits. We assume that a similar scenario might have occurred in control wards if the project had been implemented there. Thus, the analysis considers the treatment status assigned at the baseline stage, regardless of the actual receipt of project benefits during the project implementation period.

5 Results

5.1 Impact on Climate Adaptation Practices

We examine the impact of the intervention on climate adaptation practices related to crop and livestock activities. These practices are hypothesized to reduce vulnerability to climate shocks, as well as mitigate climate shocks in some cases (e.g., reduction of greenhouse gases by using more organic fertilizer and pesticides). We collect data on households' adoption of these practices during the 12 months preceding the survey. We focus on crop and livestock practices because most rural households rely on mixed crop-livestock production systems (Avis, 2018; Gautam and Andersen, 2016). Although the project promoted different practices, the mere availability of new technology or information often does not guarantee their use. The adoption of agricultural practices is influenced by factors including human capital, behavioral patterns, agro-climatic conditions, access to credit, and information (Takahashi et al., 2020; Chavas and Nauges, 2020; Magruder, 2018; Koundouri et al., 2006).

Table 2 shows that adopting soil fertility improvement practices, such as using biochar, mulching, and crop compost, is 8% lower among treatment households than control households. However, treatment households show 47% higher soil erosion (e.g., terrace, gabions, drainage, grass stripe) practices than control households, which is particularly critical in the mountainous terrain of the study area. We also find that the probability of burning crop residue on the land is five percentage points lower for the treatment households. The practice of constructing greenhouses is lower among treatment households; note that this practice is generally uncommon in the area of study. Regarding livestock activity-related practices, our findings show that treatment households practice stall feeding more frequently than control households (23 percentage points). Similarly, treatment households' reliance on outside grazing was also reduced by 32%, and fodder collection from their own land instead of the forest increased by 16 percentage points.

The overall index of climate adaptation practices shows that the project generates a 0.14 standard deviation increase in climate adaptation practices among the treatment households. However, examining individual indicators reveals nuanced impacts. Appendix Table A.6 further shows that soil fertility-related practices are lower among treated households. Conversely, soil erosion-related practices show higher adoption rates, particularly in terracing, drainage, and tree plantation activities. One explanation for such selective adaptation practices can be linked to geographical factors. Given the mountainous terrain of the study area, where landslides are frequent, households are more likely to adopt practices offering immediate benefits, contrasting with the longer-term benefits associated with soil fertility improvements.

5.2 Impact on Income, Asset, and Resilience

We examine the impact on household income, assets, and resilience. Table 3 shows impact on total income is positive and significant, amounting to a 23% increase among treatment households. Appendix Table A.7 shows that the gain in household income is driven by income from crops (58%) and enterprises (71%). Treatment households also reported 33% higher transfer income than control households. On the asset-related indicators, we find that the productive and livestock asset indexes are 52% and 48% higher for the treatment households compared to control households. However, their household or durable asset index is 29% lower. Table 3 also shows that the project positively increases resilience regardless of the indicators used. The magnitude of these impact estimates is consistent across indicators. RIMA shows about a 16% increase, CB reflects a 39% increase, and the subjective indicator demonstrates an 18% increase.

Overall, we find consistent results that the project has strengthened households' capacity to withstand and recover from adverse events. Income and asset indicators are closely associated with resilience. Income often serves as an alternative indicator of resilience, reflecting the household's ability to maintain their livelihoods. Similarly, asset accumulation reflects households' long-term capacity to cope with shocks by providing options to leverage assets during challenging times (Ansah et al., 2022; Phadera et al., 2019).

5.3 Robustness Checks

We use the post-double-selection (PDS) regression to assess the robustness of the ANCOVA results. In the ANCOVA regression, we use a fixed set of covariates based on our judgment and relevance of those indicators. Using the lasso method, the PDS method overcomes such manual covariate selection using a model-based selection process (Belloni et al., 2014). The PDS method uses the lasso estimator twice: once with the outcome variable as the dependent variable and then with the treatment variable as the dependent variable. The final set of control variables is selected based on the combined results of these two individual lasso models. Column 3 of Table 2 to Table 3 show that the PDS lasso method yields similar results to the ANCOVA ones, confirming our results are robust.

We conduct several additional robustness checks. First, we account for multiple hypothesis testing and estimate the false discovery rate (q-values) following the methodology proposed by Benjamini and Hochberg (1995) and Benjamini and Yekutieli (2005). After adjusting for multiple hypothesis testing, the results remain mostly unchanged, as shown in Appendix Tables B.4 and B.5. Second, to address the potential limitation of a relatively small sample size and number of clusters (42 wards), we employ the Randomization Inference (RI) method. This permutation-based approach allows us to assess whether the observed impact estimates could be attributed to chance. Appendix B provides a detailed explanation of the RI method. Our main results remain robust, as reported in Appendix Tables B.6 and B.7.

6 Mechanisms

We examine channels that drive the results of adopting climate adaptation practices and livelihoods. For instance, Acevedo et al. (2020) argued that the availability and effectiveness of extension services and outreach are key determinants of adopting climate-resilient crops. Other studies documented credit or risk constraints, information gaps, or lack of training as causes of lower adoption or investment in profitable technologies (Mobarak and Saldanha, 2022; Arouna et al., 2021; Atkin et al., 2017). Other studies also showcase the role of market access for smallholder farmers to adopt technology, enhance their production systems, and increase income (Ogutu et al., 2020; Pingali et al., 2019; Michelson, 2017).

We consider two sets of mechanism variables that might explain the results to explain the results of adaptation practices and resilience. The first set includes access to training and practice, social capital, and access to credit. These indicators are critical intermediate outcomes the project facilitated. The second set of mechanism variables consists of production outputs, production losses, and market access. A boost in production or lower production losses combined with increased access to the market may increase household income and resilience.

6.1 Access and Use of Training Services

The project offered training sessions for beneficiary farmers facilitated by lead farmers and resource persons to promote climate adaptation practices. Access to training does not always lead to adoption because of various factors such as human capital, behavioral patterns, environmental considerations, and practical relevance of the training (Eriksen et al., 2021). Therefore, we examine the project's impact on households receiving and implementing training services during the project period.

Table 4 shows no significant difference in receiving training services between treatment and control households at the extensive margin, but this effect becomes more pronounced at the intensive margin. The treatment households report receiving different pieces of training (training on production, marketing, climate change) by 81%. Additionally, we find a significant increase in the practice of the training services received by treatment households. Specifically, treatment households are six percentage points more likely to implement the training services they received. At the intensive margin, the boost in practice is as high as 200%. Appendix Table A.8 provides further insights into the nature of the extensions received and practiced by households. We find that increased access to and use of training is driven by training activities related to crop production and pesticide application. This result is not surprising given the project promoted the adoption of environmentally sustainable practices, such as using cow urine-based pesticides, known locally as *Jholmol*, and cow dung-based fertilizer as alternatives to chemical equivalents.

6.2 Social Capital and Access to Credit

We examine the impact of the project on social capital in terms of involvement in LAPAs (i.e., local farmer groups) and membership in economic and social groups. Table 4 indicates that treatment households are 70 percentage points more likely to be LAPA members. We find significant impacts on membership in economic groups (e.g., production, marketing, irrigation groups, etc.) and social groups (e.g., youth, women, political, or cultural groups). Further, the project has increased group membership significantly for both men (51%) and women (39%).

The bottom panel of Table 4 shows the project's impact on access to finance. The total loan amounts received by treatment households during the project period are 48% lower than control households (Table 4). Treatment households have received considerably lower loans from banks, NGO/MFIs, and informal sources (e.g., money lenders, friends, or relatives) but higher amounts from cooperatives and farmer groups. Note that the project-delivered money is not accounted for in the loan amount documented in Table 4, as the project deposited co-financing into the bank accounts of the project's target groups. Other than direct deposits, the project did not provide or facilitate loans or link households with any financial organizations.

6.3 Revenue and Production Losses

Household income can increase when earnings from production and other non-farm activities increase. Earnings can also increase through reduced production losses during harvest or post-harvest phases. Table 5 shows that the project increases revenue in farming activity by 49% and livestock activity by 68% among treatment households but not from livestock activities. We find a 331% increase in enterprise revenue for the treatment households, although enterprise activity is a rare economic activity among the sample households. A plausible explanation for this finding from anecdotal evidence is that some of the climate adaptation practices promoted by the project (e.g., irrigation systems, erosion control structures, etc.) allow households to free up time otherwise required to fetch water and build traditional erosion control structures. As a result, households have the time to engage in other income-generating opportunities such as enterprises and other non-farm activities.

We examine a set of self-reported binary indicators on production and asset losses due to climate and non-climate shocks. The survey included a comprehensive list of shocks and asked the respondents if their households lost production or assets due to these shocks. Table 5 shows that treatment households reported less household (i.e., land, household, durable) and livestock asset losses (5 percentage points) and livestock production (13 percentage points), but reportedly higher production output losses (14 percentage points).

6.4 Market Participation

We finally examine the output market participation of households (i.e., whether they sold any produced in the market). Table 5 shows a significant increase in market participation among treatment households by 20 percentage points when we consider market participation by selling any output from farming, livestock, or enterprise. Looking at the type of products households sell in the market; we find that beneficiary households are nine percentage points more likely to sell farming outputs in the market. Note that most of the farmers in the sample are subsistence farmers. Only 7% of control households sold any farming outputs in the market.

Livestock output market participation is more prevalent in our sample, with about 27% of control households participating in the livestock or livestock product market. The project further increased the livestock market participation by about 14 percentage points among treatment households. These findings highlight the project's positive impact on household output market participation. The sale of products from household enterprises is three percentage points lower among the treatment households. The project facilitated increased engagement in the market through information or connecting farmers with other farmers, underscoring the program's effectiveness in enhancing households' market orientation.

7 Additional Results

7.1 Quantifying the Role of Extreme Climate Exposure

We test whether treatment effects vary by climate shock exposure level. If treatment effects differ when we account for extreme climate conditions, it will imply that households are generally aware of climate conditions and respond to them when resources are available. We proxy climate shocks by three indicators of extreme temperature relative to their long-term averages: deviations in growing degree days (GDD), deviations in average rainfall, and deviations in maximum temperature. We draw daily maximum temperature (measured in degrees Celsius) and rainfall data (measured in millimeters) from the ECMWF Reanalysis v5 (ERA5) and Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) databases, respectively, at 5000-meter resolution near the GPS coordinate of households. We first convert temperature into GDD, a widely used measure in the existing literature on climate shocks (Amare and Balana, 2023; Jagnani et al., 2021; Lobell et al., 2011). Following the approach by Schlenker and Roberts (2009) and Amare and Balana (2023), we calculate GDD by quantifying the cumulative exposure to temperatures between a lower bound of 8 °C and an upper bound of 32 °C as given in the equation below.

$$GDD = \begin{cases} 0 & \text{if } (Temp) \leq 8°\text{C}, \\ (Temp) - 8 & \text{if } 8°\text{C} < (Temp) \leq 32°\text{C}, \\ 24 & \text{if } (Temp) > 32°\text{C}. \end{cases}$$

where $(Temp)$ represents the temperature in degrees Celsius. GDD values are aggregated year by year. We follow the same approach for HDD, where the only cut-off point is above 32 degrees Celsius. To measure the deviation for the long-term averages, we first compute the ward-level average GDD, temperature, and rainfall values from 1979 to 2018. We then subtract the household level 2019 GDD, temperature, and rainfall values from their corresponding ward-level average value.

We use the following differential treatment effects regression to estimate the effect of extreme climate exposure,

$$Y_{iwt} = \beta_0 + \beta_1 \times \mathrm{T}_w + \beta_2 \times \mathrm{C}_i + \beta_3(\mathrm{T}_w \times \mathrm{C}_i) + \beta_4 \times Y_{iw,t-1} + \mu X_{iw,t-1} + \eta \mathrm{V} + \zeta_{iwt} \quad (2)$$

where C_i is the climate shock indicator (i.e., deviation from long-term GDD, rainfall, or temperature). All other notations are the same as in equation 1. β_3 will capture the differential treatment effects of higher exposure to extreme climate. A test of β_1 + β_3 = 0 shows the treatment effects of the project among households who are exposed to mean levels of extreme climate. A test of β_1 = 0 shows the impact of the project among households without extreme climate exposure. Finally, a test of β_3 = 0 shows the differential impact of the project among households with and without extreme climate exposure.

Figure 1 summarizes the results, while Appendix Table A.9 presents detailed regression outcomes. Figure 1 shows that the project's benefits do not differ significantly based on the level of exposure to climate shocks. In other words, the project team delivered services uniformly without considering households' vulnerability to climate conditions, ensuring equal access to project benefits. This may also imply that there is no selection from the beneficiaries' side in availing the project benefits. However, the impact of the project on climate adaptation practices significantly increases when households experience extreme temperatures. The former implies that households are more inclined to adopt climate adaptation practices when they directly face the effects of climate shocks, especially when resources are available. This result also aligns with existing evidence that households adopt their choices (i.e., choice of inputs) in the presence of climate shocks (Alam et al., 2017; Aragón et al., 2021; Jagnani et al., 2021).

Furthermore, accounting for climate shock reveals a higher impact on the household income index. We find no differential impacts on asset and resilience indices concerning exposure to extreme temperatures. This may suggest that households facing severe climate conditions can maintain similar levels of resilience compared to those in less severe conditions. Note that much of the above results are found when we GDD and temperature as climate shock indicators, unlike the rainfall indicator. In fact, temperature can be the preferred indicator of climate shock compared to rainfall in the context of Nepal. Rainfall amounts have recently increased in Nepal, as illustrated in Appendix Figure A.5. This increase is viewed as a favorable climate shock at times, but heavy rainfall over consecutive days can also create damage rather than provide beneficial conditions for farmers.

7.2 Role of Different Components

The project delivered extension services and co-finance for infrastructure or production activities. The actual take-up rate and the intensity of participation may shape the project's impact. In the absence of accurate administrative data from the project, we asked respondents whether their household received any benefit or service during the project period from a list of 22 items (e.g., lead farmer contracts, improved livestock sheds, solar lighting) during the endline survey. These items are closely related to the services delivered by the project. About 92% of treatment households reported receiving at least one benefit. Control households may also receive these benefits, albeit from non-project-related sources. About 24% of control households reported receiving similar types of benefits during the project period.

We examine whether the project's impacts are correlated with the number of benefits or services received (i.e., how many distinct benefits or services were received during the project period). Appendix Figure A.6 suggests that there is no strong correlation between the number of benefits or services received by households and standardized outcome variables for the two components considered. We further explore this issue by categorizing households into two groups: low-intensity group (i.e., no benefit or one benefit) and high-intensity group (more than one benefit). We run a heterogeneous treatment effect model using Equation 2. Appendix Table A.10 shows that treatment effects on adaptation, income, asset, and resilience indexes are higher for households in the high-intensity group. Only the resilience index estimate is statistically significant. These results may suggest that the marginal benefits of receiving additional components are limited in our context and, thus, require further investigation.

We also check component-specific treatment effects. The project comprises two groups of beneficiaries: (1) training and co-finance for infrastructures and (2) training and co-finance for production activities. To accurately estimate component-specific treatment effects, one would need a multi-arm impact evaluation design, which is not the case in our study. Since the training component was available to all treatment households, and if we assume a homogeneous training effect on all households irrespective of the co-financing scheme, we can analyze the effects separately for each co-financing scheme. To do this, we first need to distinguish between households that received co-financing for infrastructure and those that received co-financing for production activities. To this end, we draw GPS coordinates of the infrastructures financed by the project. We measure the Euclidean distance between each household and the nearest infrastructure. We run an OLS regression and measure the marginal effect of distance on different outcome variables (Appendix Figure A.7).

Results show that the adaptation index increases as the distance from infrastructure increases, suggesting higher adoption among those receiving co-financing for production support. Furthermore, the difference in predicted outcomes between treatment and control households is greater as the distance increases. This may suggest that households who receive production support activities likely drive the overall project impact.[8] We do not find such large differences in income, assets, and resilience.

7.3 Cost Effectiveness

We perform a back-of-the-envelope cost-effectiveness of the project. According to the project completion report, 118,595 households directly received support from the project. The total project cost is USD 37,617,300, which translates to USD 317 per household. The project led to a 23% annual increase in household income, with an average yearly income equal to USD 826. Thus, the annual gain is about USD 190. If this income boost persists over four years, the net present value per beneficiary, with a 10% discount rate, is about USD 570. The former equals an internal rate of return of 47%. Note that we have not factored in the increase in assets or other indirect benefits from the project. Further, the benefits stemming from infrastructures, like irrigation canals,

[8] Note that infrastructure investments typically have a longer lifespan than production support activities. If we were to estimate the net present value of returns from the infrastructure and then compare it to that of the production activities group, this conclusion might change. However, such an analysis is beyond the scope of our study.

constructed by the project will likely extend beyond the four-year timeframe. We also have not considered non-target households that benefited from project-trained lead farmers or infrastructure. The actual rate of return could potentially be higher when accounting for these indirect beneficiaries.

8 Conclusion

Our study demonstrates the positive impacts of training and co-finance projects on climate adaptation practices and the livelihoods of smallholder farmers in Nepal. Factors such as access to training, social capital, and co-financing led to a boost in production and market participation. These factors are crucial in achieving these outcomes. We show that households that experienced extreme climatic shocks demonstrate higher adoption of climate adaptation practices. This suggests the project is particularly effective in assisting households facing significant climate-related challenges.

Our results highlight the significance of promoting the adoption of targeted and context-specific climate adaptation interventions to enhance resilience among vulnerable smallholder farmers. The project's targeting strategy ensured that households vulnerable to climate shocks and lacking essential information, training, and co-financing could strengthen their resilience. The project implemented local adaptation plans and support groups of vulnerable smallholder farmers in remote and mountainous areas of Nepal. Integrating production inputs effectively addressed their diverse climatic challenges and production constraints, resulting in a higher adoption rate and increased resilience. Since the project co-financed investments in infrastructures and production activities, these benefits are expected to extend beyond the project period, contributing to sustainable production and livelihoods.

Results from this study have policy implications related to climate adaptation in resource-constraint and landlocked economies such as Nepal by identifying critical, locally-specific needs and deploying resources accordingly. Governments' ability to adapt to climate conditions and coordinate with local institutions were pivotal factors in implementing and monitoring the project effectively (Nath and Behera, 2011). The engagement of local stakeholders and the contextual specificity of interventions are pivotal, particularly in developing country settings where interventions designed without close engagement with local stakeholders and contextualization can exacerbate vulnerability rather than mitigate it (Eriksen et al., 2021). The current project followed a carefully defined implementation strategy: formulation of LAPAs, building capacity of community members, mobilizing financial resources, and continuing close engagement with stakeholders. This holistic approach may contribute to successful implementation and livelihood effects among vulnerable households.

There are some limitations to this study. First, the absence of mutually exclusive treatment arms for individual project components (i.e., co-financing for infrastructure or production) limits our ability to assess their isolated effects. We show suggestive evidence based on correlation analysis that production support accompanied by training was more effective than infrastructure accompanied by training. Second, control households are located near treatment households in some cases. It is possible that they might get training information for their neighboring treatment households or from the lead farmers from neighboring areas. The former raises spillover concerns. We could not estimate the extent of the spillover effect due to the small sample size for the control group. If there are any spillover effects, it would be positive. Thus, our results may have underestimated the true project impacts. Finally, we could not quantify the impact of climate adaptation practices in terms of climate benefits (e.g., reduction in greenhouse gas emissions). These topics require extensive data collection and, thus, go beyond the scope of this study. These aspects can be of interest to future studies in this area.

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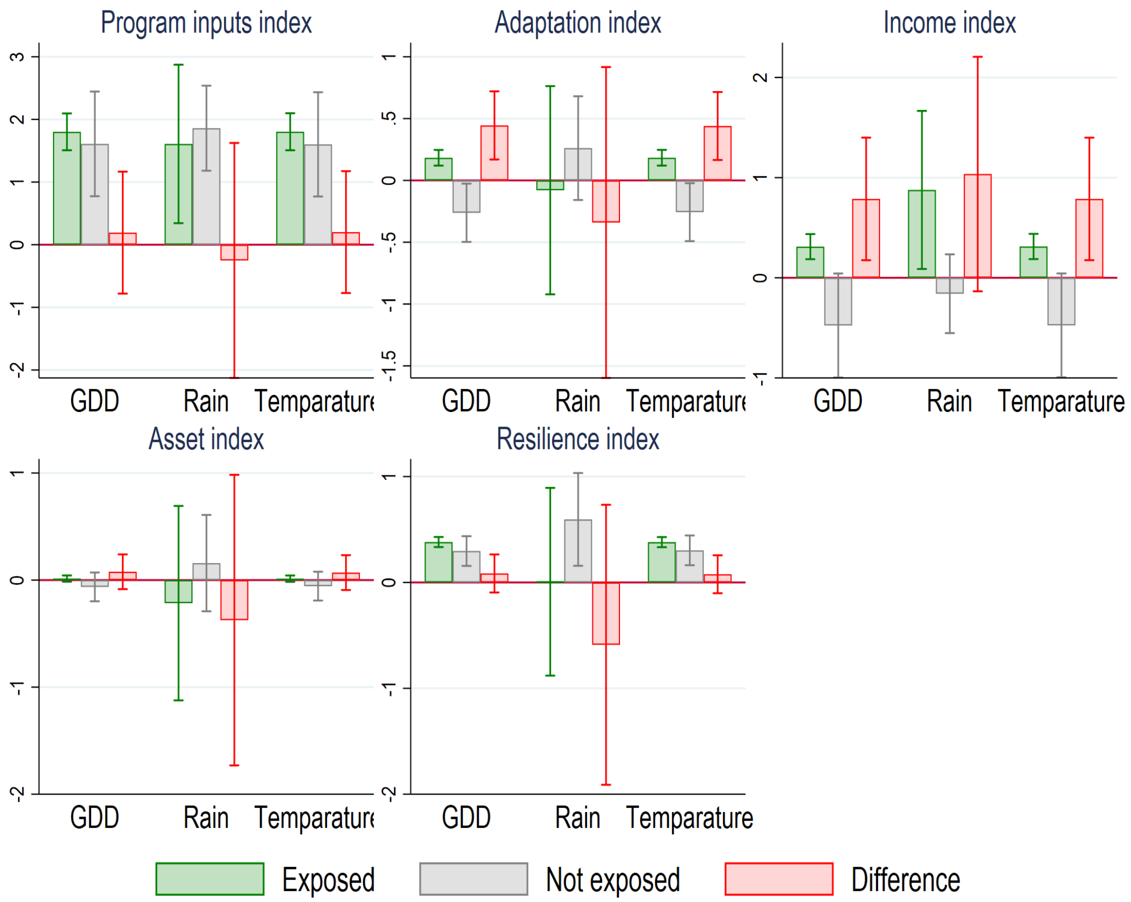

Figure 1: Climate shock exposure and outcomes

Notes: Graphs are based on Equation 2 and associated regression results in Appendix Table A.9. "Exposed" shows the treatment effect measured at the sample average GDD, rainfall, and temperature values. "Not exposed" shows the treatment effect without adjusting for GDD, rainfall, and temperature values. "Difference" shows the difference between "Exposed" and "Not exposed" groups. All the outcome variables are standardized in reference to control average and standard deviation values following Kling et al. (2007). Temperature indicators are normalized between 0 and 1. We use linear combinations of parameter tests to estimate group-wise with treatment effects and corresponding 95% confidence intervals. A linear combination test of β_1 + β_3 = 0 is shown in the "Exposed" bar. A test β_1 = 0 is shown in the "Not exposed" bar. A test of β_3 is shown in the "Difference" bar.

Table 1: Balance in Observables across Treatment Arms

	(1) All	(2) Control	(3) Treatment	(4) Mean Diff.	(5) P value
Demographics					
Number of females	2.99	3.01	2.93	-0.08	0.546
Number of males	3.11	3.08	3.21	0.13	0.296
Household Size	6.11	6.09	6.14	0.04	0.855
No. of member with primary education	3.49	3.43	3.65	0.22	0.319
No. of member with secondary education	1.94	2.00	1.78	-0.22	0.148
No. of member with graduate education	0.04	0.04	0.05	0.01	0.655
Female headed household	0.18	0.20	0.14	-0.06	0.137
Age of household head	49.32	48.72	51.07	2.35	0.224
Head with primary or less education	0.81	0.82	0.80	-0.02	0.620
Head with secondary education	0.18	0.18	0.19	0.01	0.776
Acess to infrastructure					
Electricity	0.85	0.84	0.86	0.02	0.675
Water access	0.15	0.16	0.12	-0.04	0.688
Flush toilet	0.54	0.54	0.53	-0.00	0.967
Concrete wall	0.75	0.76	0.72	-0.04	0.708
Concreate roof	0.55	0.53	0.61	0.07	0.540
Concrete floor	0.00	0.00	0.00	-0.00	0.330
Income					
Farming	38.10	39.82	33.04	-6.78	0.594
Livestock	70.89	83.85	32.71	-51.14	0.016
Enterprise	46.20	45.12	49.40	4.27	0.805
Wages/Services	588.92	583.27	605.56	22.29	0.833
Household income	744.12	752.06	720.71	-31.35	0.781
Asset holdings					
Productive	1.31	1.34	1.21	-0.14	0.297
Household	1.02	1.06	0.90	-0.16	0.106
Livestock	2.63	2.73	2.34	-0.39	0.130
Observation	1081	274	807		

Notes: Column 1 shows the average value of a variable for all households. Columns 2 and 3 show the average value of a variable for treatment and control households, respectively. Column 4 shows the mean differences in outcomes between treatment and control households. Column 5 shows the P value, estimated using linear regressions for each variable on the treatment dummy. The standard errors are clustered at the ward level (i.e., the level of treatment placement). Access to infrastructure variables is binary. Income variables are in USD and are estimated for an entire year. Asset indexes are calculated using principal component analysis. All variables are constructed using the baseline data.

Table 2: Impact on climate adaptation practices

	(1) ANCOVA	(2) LASSO	(3) Control mean	(4) Obs.
Farming practices				
Soil fertility improvment practices	-0.18**	-0.20***	2.39	1,078
	(0.075)	(0.069)		
Soil erosion reduction practices	0.21***	0.20***	0.45	1,078
	(0.034)	(0.035)		
Crop residue burned in the field	-0.05***	-0.03	0.28	1,078
	(0.017)	(0.021)		
Planted legumes between seasons	0.04*	0.06**	0.58	1,078
	(0.021)	(0.025)		
Trees or shrubs along the parcels	0.02	0.02	0.12	1,078
	(0.015)	(0.015)		
Green house on any parcels	-0.02**	-0.01	0.01	1,078
	(0.010)	(0.010)		
Livestock practices				
Have practiced stall feeding	0.23***	0.21***	0.34	1,078
	(0.022)	(0.024)		
No of months rely on grazing	-0.76***	-0.73***	2.34	1,078
	(0.194)	(0.195)		
Collect fodder mainly from own land	0.16***	0.14***	0.45	1,078
	(0.024)	(0.027)		
Adaptation index	0.14***	0.15***	0.00	1,078
	(0.025)	(0.028)		

Notes: Soil fertility improvement and soil erosion control variables are continuous. Other outcome variables are binary. The overall adaptation index is calculated as a standardized index in reference to control average and standard deviation values following Kling et al. (2007). Separate regression is estimated for each variable. The baseline value of the outcome variables is not controlled. Each regression controls household-level variables (household size; no. of members with no formal education; gender, age, and education of household head; baseline period access to electricity, drinking water, and sanitation; and baseline period improved dwelling wall and roof) as well as municipality level fixed effects. Standard errors are clustered at the ward level- the level of intervention placement. The control mean is measured as the average of an outcome variable among the control households during the endline period. Asterisks indicate the level of statistical significance: * at 10 percent; ** at 5 percent; *** at 1 percent.

Table 3: Impact on income, asset, and resilience

	(1) ANCOVA	(2) LASSO	(3) Control mean	(4) Obs.
Household income	189.32***	149.47**	809.28	1,078
	(58.455)	(60.796)		
Asset				
Productive	0.13***	0.13***	0.25	1,078
	(0.022)	(0.021)		
Household	-0.28***	-0.28***	0.98	1,078
	(0.043)	(0.054)		
Livestock	0.12***	0.05	0.25	1,078
	(0.039)	(0.043)		
Resilience				
Resilience (RIMA)	0.10***	0.09***	0.62	1,078
	(0.006)	(0.007)		
Resilience (CB)	0.23***	0.21***	0.66	935
	(0.020)	(0.019)		
Resilience (subjective)	0.11***	0.11***	0.61	1,078
	(0.012)	(0.014)		

Notes: Income variables are in USD and are estimated for an entire year. Asset indicator is calculated as an index of productive, durable, and livestock assets using principal component analysis. The definition of individual resilience indicator is given in Appendix B. The baseline value of the income and asset outcomes is controlled in regression. Each regression controls household-level variables (household size; no. of members with no formal education; gender, age, and education of household head; baseline period access to electricity, drinking water, and sanitation; and baseline period improved dwelling wall and roof) as well as municipality level fixed effects. Standard errors are clustered at the ward level- the level of intervention placement. The control mean is measured as the average of an outcome variable among the control households during the endline period. Asterisks indicate the level of statistical significance: * at 10 percent; ** at 5 percent; *** at 1 percent.

Table 4: Impact on intermediate outcomes/mechanisms

	(1) ANCOVA	(2) LASSO	(3) Control mean	(4) Obs.
Training				
Received at least one training	0.02	0.04*	0.07	1,078
	(0.015)	(0.021)		
Number of different trainings received	0.09**	0.15***	0.11	1,078
	(0.039)	(0.047)		
Practiced at least one tranining	0.06***	0.08***	0.05	1,078
	(0.014)	(0.018)		
Number of different trainings practiced	0.16***	0.21***	0.08	1,078
	(0.035)	(0.041)		
Social capital				
Household has a member in LAPA group	0.70***	0.72***	0.00	1,078
	(0.013)	(0.016)		
Economic groups	0.30***	0.31***	0.55	1,078
	(0.019)	(0.030)		
Social groups	0.36***	0.39***	0.51	1,078
	(0.025)	(0.022)		
No. of men in different groups	0.31***	0.28***	0.61	1,078
	(0.049)	(0.059)		
No. of women in different groups	0.41***	0.47***	1.04	1,078
	(0.051)	(0.049)		
Access to loans				
Total	-627.61***	-574.65***	1321.78	1,078
	(94.518)	(116.581)		
Bank	-102.48*	-158.30**	189.45	1,078
	(59.954)	(75.828)		
NGO/MFI	-543.25***	-525.32***	121.89	1,078
	(20.540)	(28.366)		
Cooperative	209.32***	206.10***	157.69	1,078
	(40.400)	(56.343)		
Informal	-199.03***	-108.97	857.78	1,078
	(63.053)	(67.024)		

Notes: Variable definitions are available in Appendix B. Training related indicators are binary (i.e., received or practiced at least one...) and continuous (i.e., Number of ..). Social capital-related indicators are both binary (i.e., LAPA group, economic, social) and continuous (i.e., No. of ..) in nature. Loan variables are in USD and are estimated for an entire year. Separate regression is estimated for each variable. The baseline value of the outcome variables is not controlled. Each regression controls household-level variables (household size; no. of members with no formal education; gender, age, and education of household head; baseline period access to electricity, drinking water, and sanitation; and baseline period improved dwelling wall and roof) as well as municipality level fixed effects. Standard errors are clustered at the ward level- the level of intervention placement. The control mean is measured as the average of an outcome variable among the control households during the endline period. Asterisks indicate the level of statistical significance: * at 10 percent; ** at 5 percent; *** at 1 percent.

Table 5: Impact on intermediate outcomes/mechanisms

	(1) ANCOVA	(2) LASSO	(3) Control mean	(4) Obs.
Revenue				
Farming	92.83***	80.70***	189.75	1,078
	(10.948)	(9.204)		
Livestock	90.86***	-1.73	134.01	1,078
	(21.676)	(43.926)		
Enterprise	6.93***	7.06***	2.11	1,078
	(0.424)	(0.555)		
Asset and Production loss				
Household asset	-0.05**	-0.06**	0.20	1,078
	(0.023)	(0.025)		
Livestock asset	-0.13***	-0.13***	0.04	1,078
	(0.011)	(0.015)		
Production	0.14***	0.15***	0.70	1,078
	(0.019)	(0.027)		
Market particiaption				
Any	0.20***	0.15***	0.34	1,078
	(0.029)	(0.032)		
Crop	0.09***	0.08***	0.07	1,078
	(0.016)	(0.016)		
Livestock	0.14***	0.08***	0.27	1,078
	(0.029)	(0.031)		
Enterprise	-0.03**	-0.04**	0.07	1,078
	(0.013)	(0.015)		

Notes: Variable definitions are available in Appendix B. Revenue variables are in USD and are estimated for an entire year. Asset and production losses and market participation variables are binary. Separate regression is estimated for each variable. The baseline value of the outcome variables is not controlled. Each regression controls household-level variables (household size; no. of members with no formal education; gender, age, and education of household head; baseline period access to electricity, drinking water, and sanitation; and baseline period improved dwelling wall and roof) as well as municipality level fixed effects. Standard errors are clustered at the ward level- the level of intervention placement. The control mean is measured as the average of an outcome variable among the control households during the endline period. Asterisks indicate the level of statistical significance: * at 10 percent; ** at 5 percent; *** at 1 percent.

Building Climate Resilience among Small-scale Producers in Nepal: The Impact of an Integrated Development Program

Marup Hossain, Gowthami Venkateswaran, and Tisorn Songsermsawas

Online Appendix

A Figures and Tables

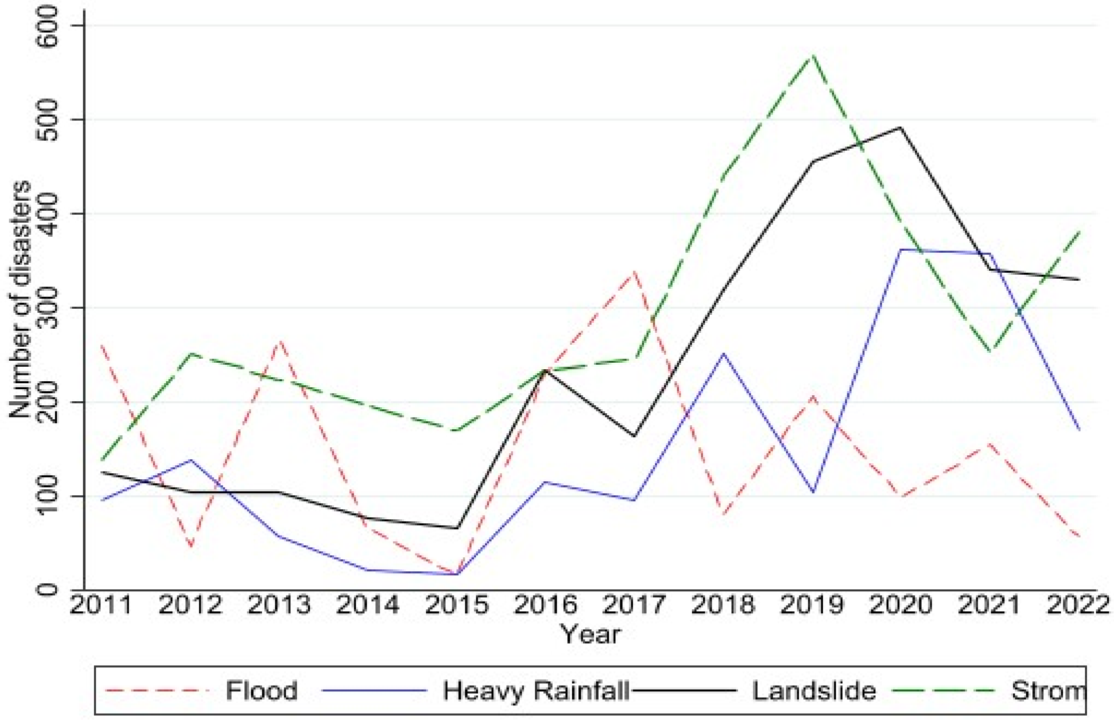

Figure A.1: Natural disasters over time in Nepal

Notes: Graph shows the total number of different shocks reported by year in the Nepal disaster risk reduction portal. Records are available at http://drrportal.gov.np/.

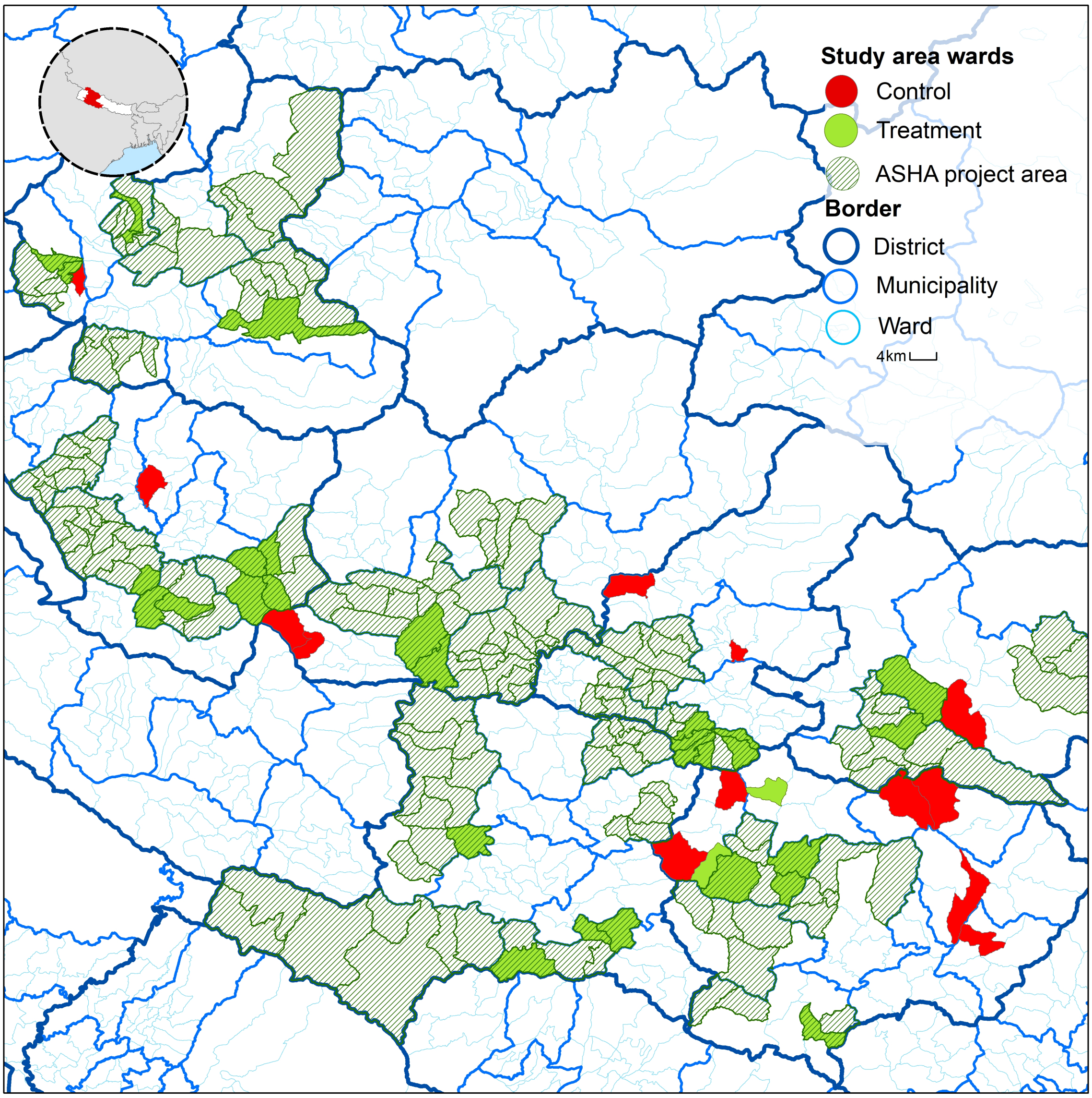

Figure A.2: Study area map

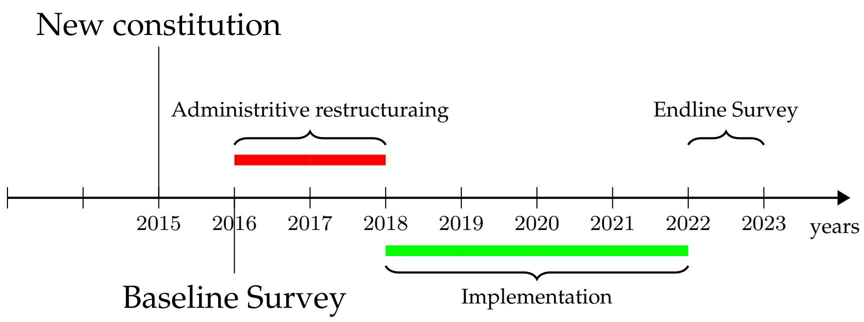

Figure A.3: ASHA project geographical coverage

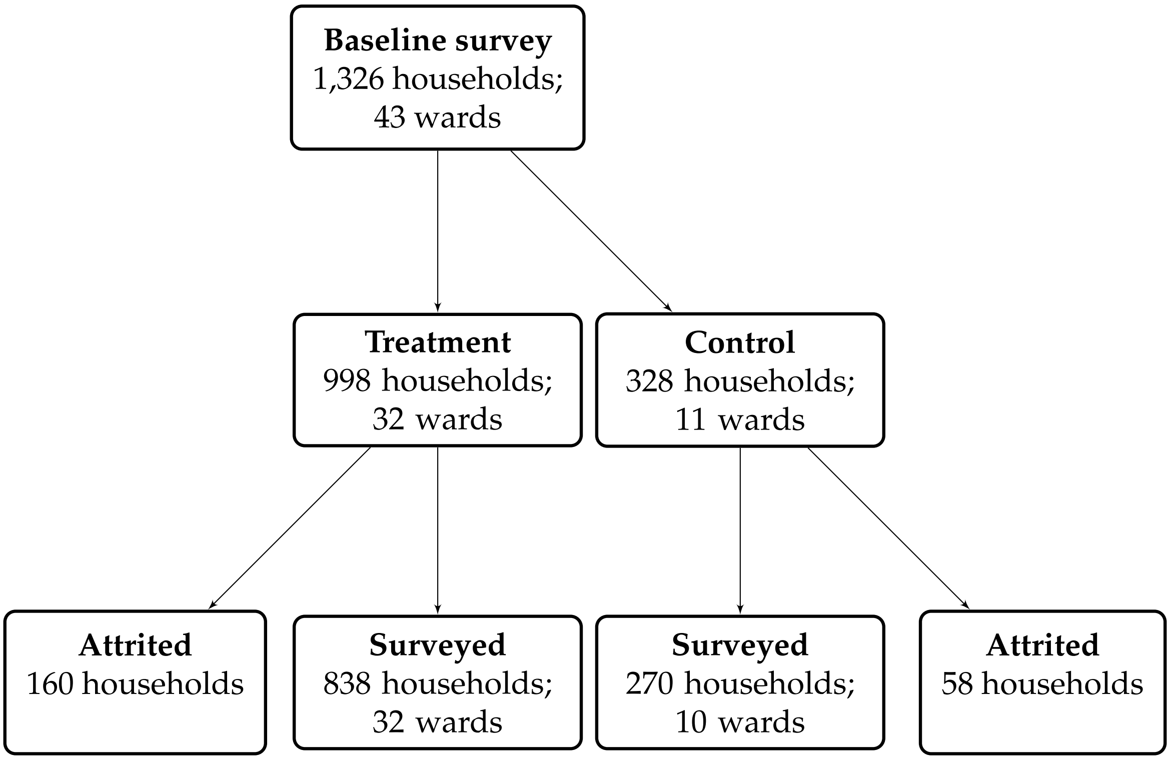

Figure A.4: ASHA project sampling framework

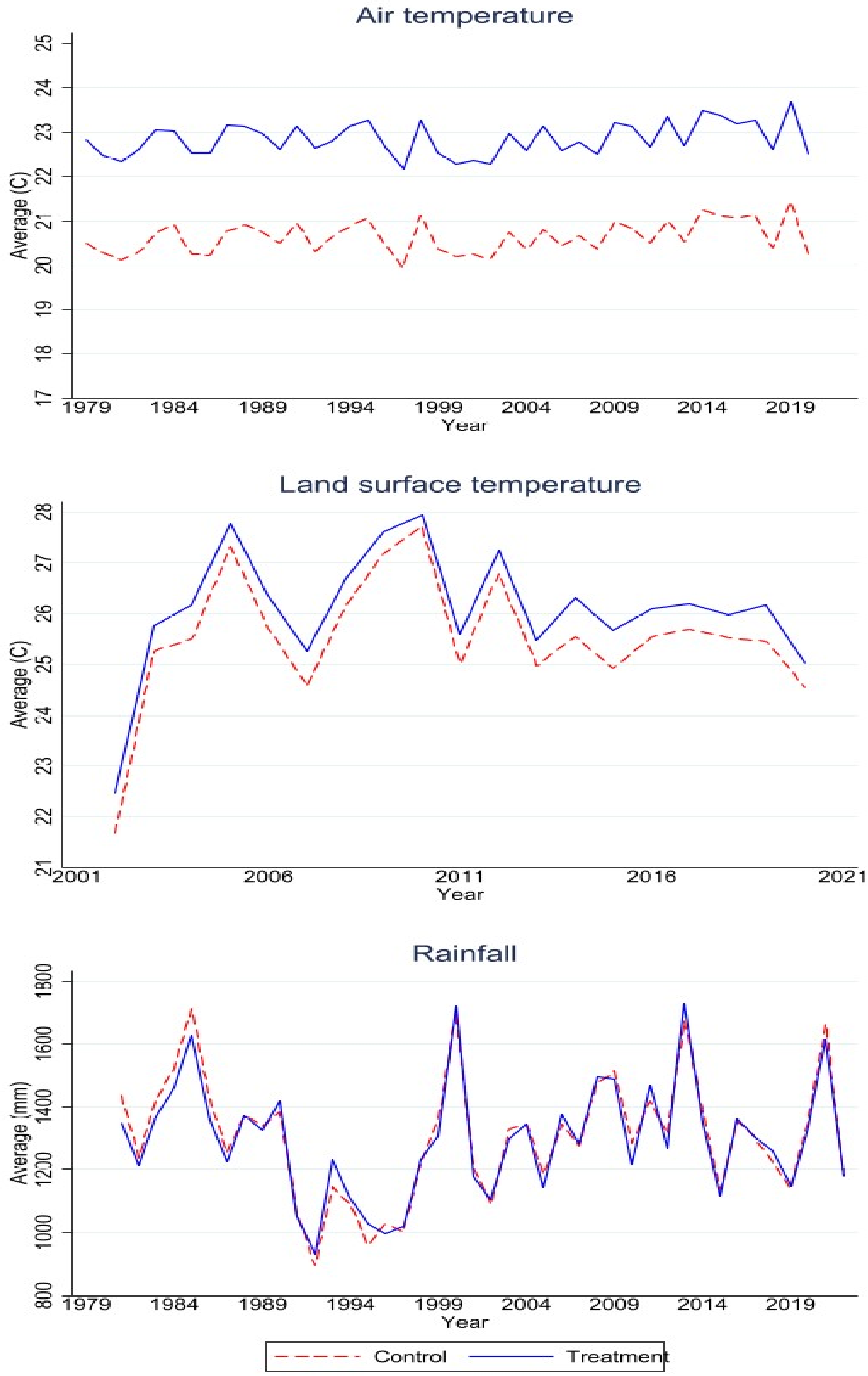

Figure A.5: Temperature and rainfall in the study area over time

Notes: Graphs show temperature and rainfall amounts over the year in the study area. Data is recorded at each household GPS location point. Air temperature data is drawn from the ERA5 hourly data series. Land surface temperature is drawn from MODIS/Terra Land Surface Temperature/3-Band Emissivity Daily data. Finally, rainfall data is drawn from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS).

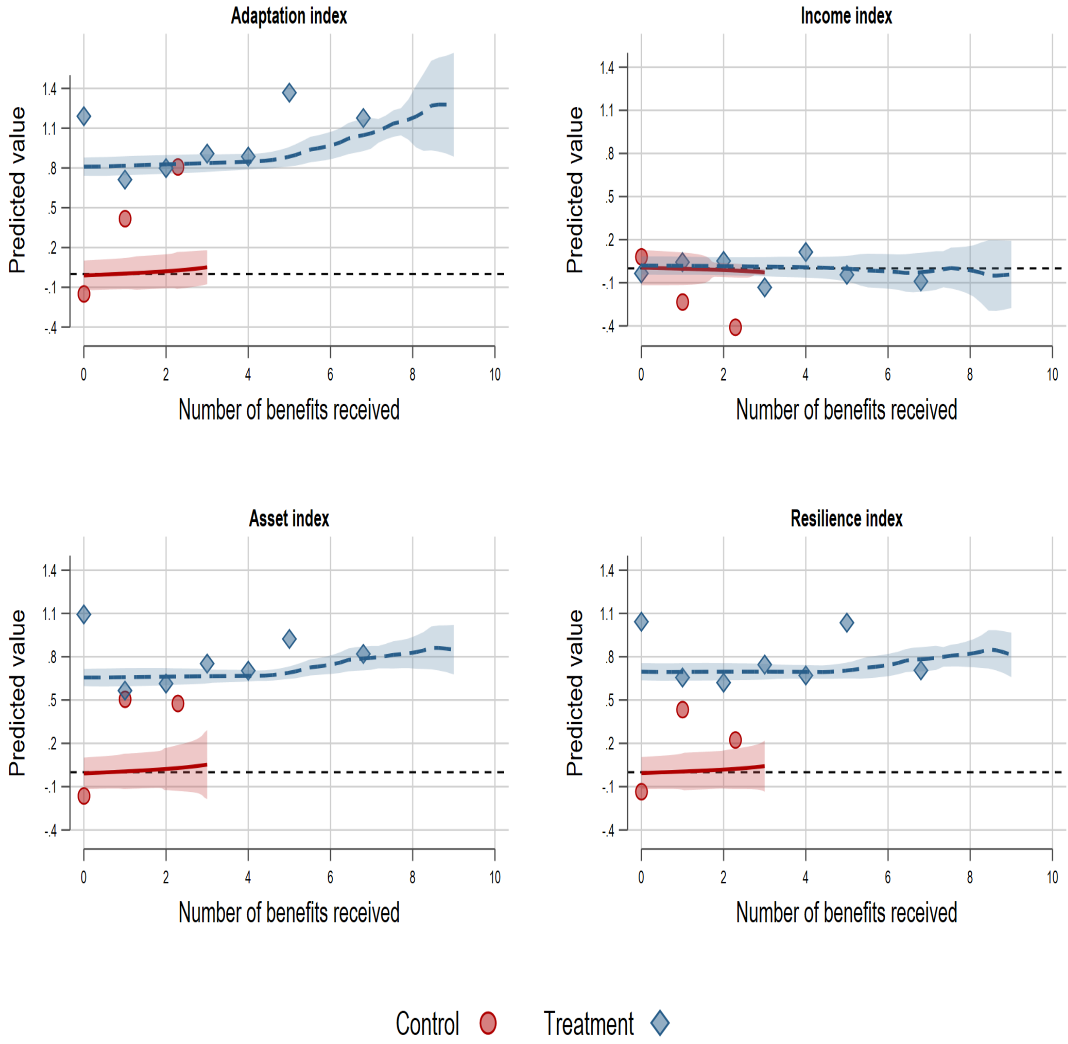

Figure A.6: Association between program intensity and outcomes

Notes: Graphs plot scatter points and quadratic fit lines for treatment and control households separately.

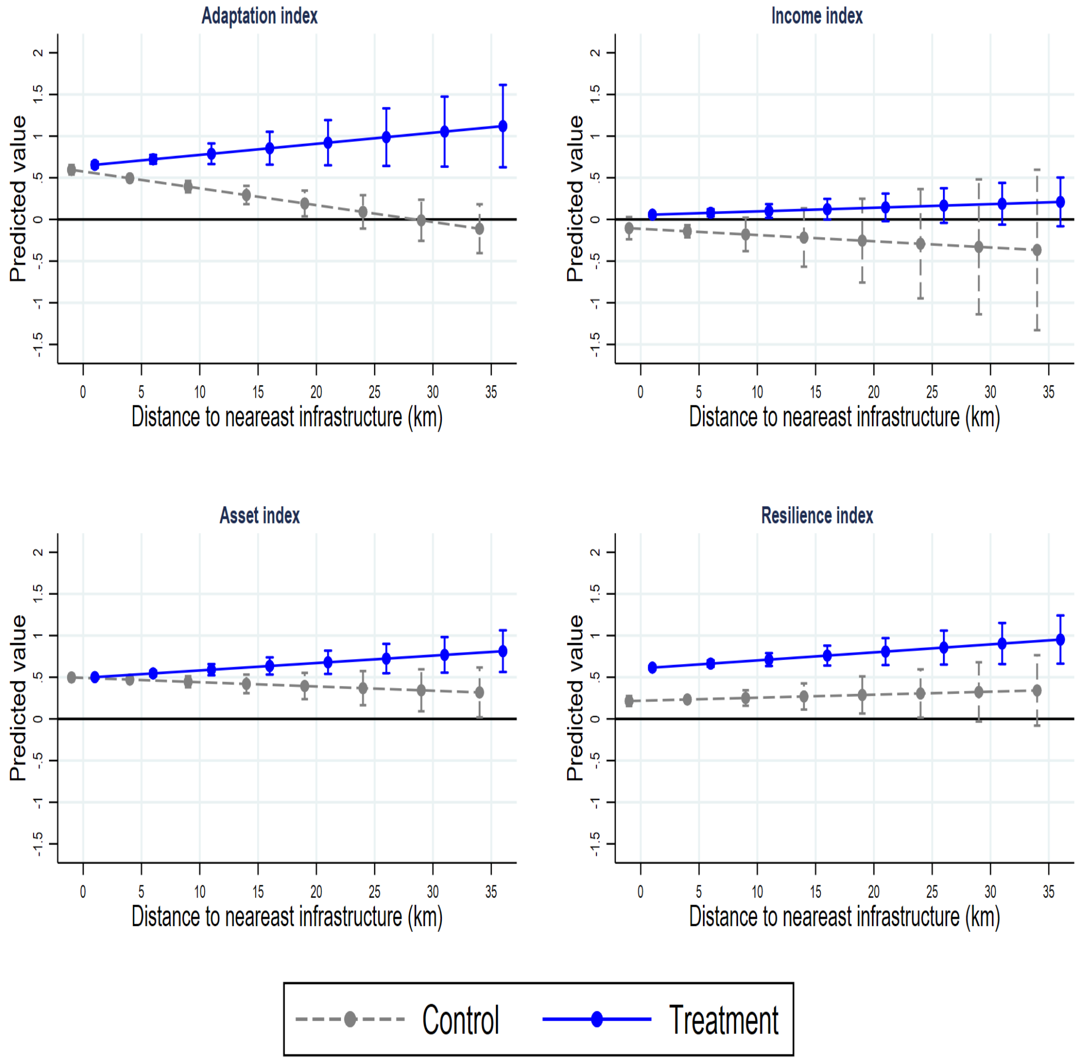

Figure A.7: Marginal effect of distance to project built infrastructure on outcomes

Notes: Figure shows the marginal effect of distance along with 95% confidence interval on different outcome indexes. All the outcome variables are standardized in reference to the average and standard deviation values of the control households. Each regression controls household-level variables (household size; no. of members with no formal education; gender, age, and education of household head; baseline period access to electricity, drinking water, and sanitation; and baseline period improved dwelling wall and roof) as well as VDC level fixed effects. Standard errors are clustered at the ward level- the level of intervention placement.

Table A.1: Sample distribution by districts

	Baseline		Endline	
	Treatment	Control	Treatment	Control
Dailekh	251	0	187	0
Jajarkot	49	49	41	38
Kalikot	132	14	110	11
Rolpa	227	138	187	120
Rukum	208	127	189	101
Salyan	131	0	124	0
Total	998	328	838	270

Notes: Baseline consists of households from the treatment and control (due to restructuring) wards surveyed in 2016. Endline consists of households from the treatment and control (due to restructuring) wards, with a completed endline survey in 2022. Rukum West and Rukum East are considered as one district.

Table A.2: Determinants of endline attrition

	(1) Attrition	(2) Attrition
Treatment	-0.017	-0.010
	(0.031)	(0.028)
Household Size		0.264
		(0.356)
Number of females		-0.271
		(0.353)
Number of males		-0.246
		(0.356)
No. of member with primary education		-0.019
		(0.015)
No. of member with secondary education		-0.011
		(0.018)
No. of member with graduate education		0.022
		(0.057)
Female headed household		-0.028
		(0.028)
Age of household head		-0.003***
		(0.001)
Head with primary or less education		0.126
		(0.125)
Head with secondary education		0.097
		(0.128)
Electricity		-0.037
		(0.031)
Water access		0.010
		(0.035)
Flush toilet		-0.043*
		(0.025)
Concrete wall		0.015
		(0.020)
Concrete roof		0.029
		(0.027)
Concrete floor		-0.273***
		(0.047)
Productive		-0.002
		(0.010)
Household		0.004
		(0.012)
Livestock		-0.019
		(0.014)
Income from farming		-0.000
		(0.000)
Income from livestock		-0.000***
		(0.000)
Income from enterprise		0.000
		(0.000)
Income from wages or salaries		0.000
		(0.000)
Constant	0.177***	0.326**
	(0.025)	(0.121)
Observations	1,326	1,325
R-squared	0.000	0.040

Notes: Attrition indicates whether households were not found or households did not agree to be interviewed during the endline. OLS regression is used and standard errors are clustered at the ward level- the level of intervention placement. Asterisks indicate the level of statistical significance: * at 10 percent; ** at 5 percent; *** at 1 percent.

Table A.3: Balance in Observables across Treatment Arms

	(1) All	(2) Control	(3) Treatment	(4) Mean Diff.	(5) P value
Demographics					
Number of females	3.00	3.03	2.93	-0.10	0.480
Number of males	3.11	3.07	3.21	0.13	0.280
Household Size	6.11	6.10	6.14	0.04	0.881
No. of member with primary education	3.48	3.42	3.65	0.23	0.292
No. of member with secondary education	1.96	2.02	1.78	-0.24	0.112
No. of member with graduate education	0.04	0.04	0.05	0.01	0.609
Female headed household	0.19	0.21	0.14	-0.07	0.085
Age of household head	49.18	48.56	51.07	2.51	0.194
Head with primary or less education	0.81	0.82	0.80	-0.02	0.584
Head with secondary education	0.18	0.18	0.19	0.01	0.733
Acess to infrastructure					
Electricity	0.85	0.84	0.86	0.02	0.647
Water access	0.15	0.16	0.12	-0.04	0.654
Flush toilet	0.54	0.54	0.53	-0.01	0.942
Concreate wall	0.76	0.77	0.72	-0.05	0.646
Concreate roof	0.54	0.52	0.61	0.09	0.461
Concreate floor	0.00	0.00	0.00	-0.00	0.329
Income					
Farming	38.88	40.78	33.04	-7.74	0.541
Livestock	72.17	85.07	32.71	-52.36	0.013
Enterprise	48.80	48.61	49.40	0.79	0.964
Wages/Services	597.38	594.70	605.56	10.86	0.919
Total	757.22	769.16	720.71	-48.45	0.671
Asset holdings					
Productive	1.36	1.42	1.21	-0.21	0.132
Household	1.06	1.11	0.90	-0.21	0.040
Livestock	2.66	2.76	2.34	-0.42	0.103
Observation	1112	274	838		

Notes: Column 1 shows the average value of a variable for all households. Columns 2 and 3 show the average value of a variable for treatment and control households, respectively. Column 4 shows the mean differences in outcomes between treatment and control households. Column 5 shows the P value, estimated using linear regressions for each variable on the treatment dummy. The standard errors are clustered at the ward level (i.e., the level of treatment placement). Access to infrastructure variables is binary. Income variables are in USD and are estimated for an entire year. Asset indexes are calculated using principal component analysis. All variables are constructed using the baseline data.

Table A.4: Ward level balance in baseline

	(1) All	(2) Control	(3) Treatment	(4) Mean Diff.	(5) P value
Road density	2.12	2.06	2.30	0.24	0.521
Range land area	193,748.40	188,840.55	208,025.79	19,185.24	0.882
Elevation	1,766.56	1,714.59	1,917.75	203.17	0.203
Travel time to nearest city (minutes)	113.99	106.72	135.17	28.45	0.321
Observation	43	11	32		

Notes: Column 1 shows the average value of a variable for all wards. Columns 2 and 3 show the average value of a variable for retained and dropped wards, respectively. Column 4 shows the mean differences in outcomes between retained and dropped wards. Column 5 shows the P value, estimated using linear regressions for each variable on the treatment dummy.

Table A.5: Summary statistics

	(1) All Mean	(2) SD	(3) Control Mean	(4) SD	(5) Treatment Mean	(6) SD
Demographics						
Number of females	2.28	1.23	2.27	1.22	2.31	1.27
Number of males	1.88	1.15	1.85	1.16	1.97	1.11
Household Size	4.17	1.85	4.12	1.85	4.30	1.86
No. of member with primary education	2.14	1.16	2.09	1.14	2.29	1.21
No. of member with secondary education	1.53	1.26	1.54	1.24	1.50	1.31
No. of member with graduate education	0.05	0.24	0.05	0.24	0.05	0.23
Female headed household	0.35	0.48	0.36	0.48	0.31	0.46
Age of household head	50.42	14.37	50.24	14.27	50.95	14.70
Head with primary or less education	0.75	0.43	0.74	0.44	0.78	0.42
Head with secondary education	0.23	0.42	0.24	0.43	0.20	0.40
Acess to infrastructure						
Electricity	0.82	0.39	0.80	0.40	0.86	0.35
Water access	0.95	0.21	0.95	0.23	0.98	0.13
Flush toilet	0.83	0.38	0.80	0.40	0.91	0.29
Concrete wall	0.80	0.40	0.77	0.42	0.89	0.32
Concreate roof	0.18	0.39	0.15	0.36	0.29	0.45
Concrete floor	0.01	0.12	0.02	0.13	0.01	0.10
Benefits and adoption						
Total no. of benefits received	1.57	1.56	2.01	1.54	0.28	0.53
Soil fertility initiatives	2.43	1.47	2.45	1.53	2.39	1.27
Soil erosion control initiatives	0.59	0.73	0.64	0.74	0.45	0.66
Resilience						
Resilience (RIMA)	0.64	0.13	0.64	0.13	0.62	0.12
Resilience (CB)	0.73	0.42	0.76	0.41	0.66	0.46
Resilience (subjective)	0.68	0.29	0.70	0.27	0.61	0.32
Income						
Farming	187.42	201.36	194.65	217.27	166.11	142.90
Livestock	165.31	571.66	185.61	648.32	105.52	216.91
Enterprise	60.15	359.57	53.41	286.85	80.00	517.69
Wages/Services	413.06	834.66	397.93	795.04	457.64	941.89
Household income	825.93	1,178.04	831.59	1,153.24	809.28	1,250.29
Asset holdings						
Productive	0.26	0.57	0.26	0.62	0.25	0.38
Household	0.98	1.03	0.98	1.04	0.98	1.03
Livestock	0.34	0.55	0.37	0.62	0.25	0.26
Sales, credit, and social capital						
Total sales	336.03	1,715.87	322.65	1,407.51	375.42	2,407.58
Total loans obtained	1,104.12	2,151.85	1,030.21	2,098.15	1,321.78	2,292.92
Member of a group	0.86	0.34	0.86	0.34	0.86	0.34
Observation	1081		274		807	

Notes: Columns 1 and 2 show the average and standard deviation values for the full sample. Columns 3 and 4 show the same statistics for the control households, and columns 5 and 6 do the same for the treatment households. Access to infrastructure variables is binary. Income variables are in USD and are estimated for an entire year. Asset indexes are calculated using principal component analysis. Income variables are in USD and are estimated for an entire year.

Table A.6: Impact on climate adaptation practices

	(1) ANCOVA	(2) LASSO	(3) Control mean	(4) Obs.
Soil fertility				
Use biochar	-0.04	-0.06*	0.48	1,078
	(0.036)	(0.037)		
Use mulchingfor	-0.01	-0.01	0.12	1,078
	(0.026)	(0.026)		
Use crop compost	-0.13***	-0.13***	1.79	1,078
	(0.047)	(0.049)		
Soil erosion				
Terrace	0.04**	0.02	0.36	1,078
	(0.016)	(0.022)		
Gabions/sandbag	0.00	0.01*	0.00	1,078
	(0.004)	(0.005)		
Drainage/ditches	0.08***	0.08***	0.01	1,078
	(0.006)	(0.005)		
Trees	0.10***	0.09***	0.06	1,078
	(0.019)	(0.018)		
Bushes	-0.00	-0.00	0.00	1,078
	(0.006)	(0.006)		
Grass strips	-0.00	0.00	0.01	1,078
	(0.007)	(0.007)		

Notes: All outcome variables are binary. Separate regression is estimated for each variable. The baseline value of the outcome variables is not controlled. Each regression controls household-level variables (household size; no. of members with no formal education; gender, age, and education of household head; baseline period access to electricity, drinking water, and sanitation; and baseline period improved dwelling wall and roof) as well as municipality level fixed effects. Standard errors are clustered at the ward level- the level of intervention placement. The control mean is measured as the average of an outcome variable among the control households during the endline period. Asterisks indicate the level of statistical significance: * at 10 percent; ** at 5 percent; *** at 1 percent.

Table A.7: Impact on income

	(1) ANCOVA	(2) LASSO	(3) Control mean	(4) Obs.
Farming	97.21***	85.67***	166.11	1,078
	(9.379)	(8.518)		
Livestock	9.97	-7.39	105.52	1,078
	(42.412)	(44.207)		
Enterprise	57.43***	48.54***	80.00	1,078
	(14.401)	(14.908)		
Wages/Services	7.99	22.66	457.64	1,078
	(37.209)	(41.710)		
Transfers	278.51***	302.56***	852.05	1,078
	(39.167)	(41.094)		

Notes: Income variables are in USD and are estimated for an entire year. The baseline value of the income is controlled in regression. Each regression controls household-level variables (household size; no. of members with no formal education; gender, age, and education of household head; baseline period access to electricity, drinking water, and sanitation; and baseline period improved dwelling wall and roof) as well as municipality level fixed effects. Standard errors are clustered at the ward level- the level of intervention placement. The control mean is measured as the average of an outcome variable among the control households during the endline period. Asterisks indicate the level of statistical significance: * at 10 percent; ** at 5 percent; *** at 1 percent.

Table A.8: Impact on training receipt and practice

	(1) ANCOVA	(2) LASSO	(3) Control mean	(4) Obs.
Received training				
Production	0.07***	0.08***	0.03	1,078
	(0.013)	(0.016)		
Pesticide or chemical use	0.04	0.07**	0.04	1,078
	(0.026)	(0.029)		
Harvesting	-0.00	0.00	0.01	1,078
	(0.007)	(0.008)		
Livestock	-0.02	-0.01	0.02	1,078
	(0.015)	(0.016)		
Forestry	0.00	0.00	0.00	1,078
	(0.007)	(0.006)		
Marketing	-0.00	-0.00	0.00	1,078
	(0.002)	(0.002)		
Credit or financial managment	0.00	0.00	0.00	1,078
	(0.003)	(0.003)		
Practiced training				
Production	0.10***	0.10***	0.01	1,078
	(0.013)	(0.015)		
Pesticide or chemical use	0.10***	0.14***	0.04	1,078
	(0.022)	(0.025)		
Harvesting	-0.01	-0.00	0.01	1,078
	(0.007)	(0.007)		
Livestock	-0.03*	-0.02	0.01	1,078
	(0.014)	(0.016)		
Forestry	-0.01	-0.00	0.00	1,078
	(0.004)	(0.004)		
Marketing	-0.00	-0.00	0.00	1,078
	(0.002)	(0.002)		
Credit or financial managment	0.00	0.00	0.00	1,078
	(0.003)	(0.003)		

Notes: All outcome variables are binary. Separate regression is estimated for each variable. The baseline value of the outcome variables is not controlled. Each regression controls household-level variables (household size; no. of members with no formal education; gender, age, and education of household head; baseline period access to electricity, drinking water, and sanitation; and baseline period improved dwelling wall and roof) as well as municipality level fixed effects. Standard errors are clustered at the ward level- the level of intervention placement. The control mean is measured as the average of an outcome variable among the control households during the endline period. Asterisks indicate the level of statistical significance: * at 10 percent; ** at 5 percent; *** at 1 percent.

Table A.9: Role of climate shocks

	(1) Program inputs index	(2) Adaptation index	(3) Income index	(4) Asset index	(5) Resilience index	(6) Program inputs index	(7) Adaptation index	(8) Income index	(9) Asset index	(10) Resilience index	(11) Program inputs index	(12) Adaptation index	(13) Income index	(14) Asset index	(15) Resilience index
Treatment	1.757***	-0.195	-0.304	-0.072	0.271***	2.035***	0.289	0.038	0.140	0.568**	1.749***	-0.190	-0.304	-0.065	0.278***
	(0.384)	(0.125)	(0.279)	(0.069)	(0.072)	(0.301)	(0.220)	(0.203)	(0.236)	(0.228)	(0.383)	(0.125)	(0.278)	(0.069)	(0.072)
Deviation in GDD	-0.285	3.620***	-1.309**	4.005***	3.658***										
	(0.524)	(0.190)	(0.536)	(0.153)	(0.116)										
Treatment X Deviation in GDD	0.668	0.911***	1.708**	0.178	0.210										
	(0.949)	(0.310)	(0.689)	(0.169)	(0.178)										
Deviation in Rain						-0.579	3.916***	-0.536	3.955***	3.671***					
						(0.823)	(0.698)	(0.659)	(0.905)	(0.807)					
Treatment X Deviation in Rain						-0.044	-0.498	1.681*	-0.613	-0.967					
						(1.445)	(1.056)	(0.971)	(1.129)	(1.090)					
Deviation in Temparature											-0.308	3.914***	-1.416**	4.331***	3.956***
											(0.567)	(0.206)	(0.580)	(0.165)	(0.126)
Treatment X Deviation in Temparature											0.744	0.971***	1.846**	0.174	0.209
											(1.023)	(0.333)	(0.743)	(0.184)	(0.192)
Constant	0.134	-1.171***	0.754**	-1.375***	-1.605***	0.226	-0.690**	0.159	-0.663	-0.982**	0.134	-1.171***	0.754**	-1.376***	-1.606***
	(0.341)	(0.124)	(0.349)	(0.099)	(0.076)	(0.394)	(0.334)	(0.316)	(0.434)	(0.387)	(0.342)	(0.124)	(0.349)	(0.099)	(0.076)
Observations	1,081	1,081	1,081	1,081	1,081	1,081	1,081	1,081	1,081	1,081	1,081	1,081	1,081	1,081	1,081
R-squared	0.48	0.75	0.17	0.98	0.83	0.48	0.65	0.17	0.85	0.72	0.48	0.75	0.17	0.98	0.83

Notes: Each column shows results from a separate ANCOVA regression. Growing degree days (GDD) and rainfall are continuous variables. Adaptation and resilience are standardized indexes. Each regression controls for the baseline value of the dependent variable as well as household-level variables (household size; no. of members with primary education and graduate education; gender, age, and education of household head; baseline period access to electricity, drinking water, and sanitation; and baseline period improved dwelling wall and roof) as well as fixed effects for VDC. Standard errors are clustered at the ward level- the level of intervention placement. Asterisks indicate the level of statistical significance: * at 10 percent; ** at 5 percent; *** at 1 percent.

Table A.10: Impact of the project by the intensity of the benefits

VARIABLES	(1) Adaptation index	(2) Income index	(3) Asset index	(4) Resilience index
Treatment	0.135***	0.145**	0.005	0.354***
	(0.040)	(0.061)	(0.028)	(0.027)
Multiple benefits	0.075	-0.550*	-0.231	-0.555***
	(0.160)	(0.312)	(0.245)	(0.132)
Multiple benefits X Treatment	-0.026	0.539	0.240	0.515***
	(0.184)	(0.323)	(0.250)	(0.143)
Constant	0.928***	-0.051	1.154***	0.756***
	(0.097)	(0.124)	(0.069)	(0.100)
Observations	1,081	1,081	1,081	1,081
R-squared	0.61	0.21	0.79	0.67

Notes: ”Multiple benefits” is a binary indicator that equals one if a household receives more than one benefit from the project and 0 otherwise. Each regression controls for the baseline value of the dependent variable as well as household-level variables (household size; no. of members with primary education and graduate education; gender, age, and education of household head; baseline period access to electricity, drinking water, and sanitation; and baseline period improved dwelling wall and roof) as well as fixed effects for VDC. Standard errors are clustered at the ward level- the level of intervention placement. Asterisks indicate the level of statistical significance: * at 10 percent; ** at 5 percent; *** at 1 percent.

Appendix B

B Variable Construction

Table B.1: Indicators on climate adaptation practices

Indicator	Description	Type
Soil fertility improvement	Number of techniques (e.g., Biochar, Mulching, and Crop compost) used to improve soil condition	Continuous
Soil erosion control	Techniques (e.g., Terrace, Gabions/drainage, and Trees/bushes/grass) used to control soil erosion	Continuous
Residue burned	Burned crop residue on the field	Binary
Legumes between seasons	Planted any legumes such as broad bean, beans, lentils, peas before or after on the same land	Binary
Trees or shrubs	Any other types of trees or shrubs on any of your parcels, including trees or shrubs planted along the plots' borders	Binary
Greenhouse	Greenhouses or plastic houses on any of the plots	Binary
Stall feeding	Household practice stall feeding for livestock	Binary
No of months rely on grazing	Household primarily relied on grazing livestock outside	Continuous
Collect fodder mainly from own land	Household collected fodder mainly from own land instead of forest	Binary

B.1 Resilience Indicators

We use three alternative indicators of resilience. The first indicator is the Resilience Indicators for Measurement and Analysis II (RIMA) developed by the Food and Agricultural Organization (FAO, 2023). We complemented this indicator with another objective indicator proposed by Cissé and Barrett (2018) and a subjective indicator following Jones and d'Errico (2019). Below, we detail the calculation methods of each indicator.

B.1.1 Resilience RIMA

RIMA is the most commonly used index to measure resilience quantitatively (Upton et al., 2022). It is a latent variable (η) jointly estimated by its causes and indicators and estimates an overall resilience capacity index (RCI) using two models: formative (causes) and reflective (indicators).

1. The formative model involves a hypothesis that resilience (η) is influenced by the pillars (X). The pillars are 1) Access to Basic Services (ABS), Assets (AS), Social Safety Nets (SSN), and Adaptive Capacity (AC). Each pillar consists of indicators shown in Table B.2.

$$\eta = \gamma' X + \epsilon$$

2. The reflective model links resilience (η) with resilience indicators:

$$Y = \lambda \eta + \zeta$$

   where $(y_1, y_2, ...y_n)$ are indicators of the latent variable η. We used the well-being score (household satisfaction with their current economic condition), food sufficiency score (number of months with sufficient food), and income as resilience indicators.

A structural equation model called the Multiple Causes Multiple Indicators (MIMIC) can be used to measure the Resilience Capacity Index (RCI). We estimate the RCI score separately for the baseline and endline. Finally, we normalized the RCI score such that it ranges between 0 to 1.

B.1.2 Resilience Cissé and Barrett (2018)

The CB method employs ordinary least squares (OLS) regression to estimate household-level conditional mean and variance of wellbeing (i.e., income). With an appropriate distributional assumption (e.g., beta, exponential, gamma, normal, student-t), the conditional probability of maintaining a minimum level of well-being (i.e., above the average value of national income level) can be calculated using the estimated mean and variance from the OLS regression. We detail the steps below:

1. Run OLS regression to estimate the conditional mean of well-being (W).

$$W_{it} = \sum_{k=1}^{4} \alpha_k W_{i,t-1}^k + \gamma X_{it} + \mu S_{it} + \zeta_{it}$$

   where W_{it} and $W_{i,t-1}$ stands for endline and baseline income of household i, respectively. k indicates the fourth-order polynomial of baseline income to allow for possible nonlinear dynamics. X contains household characteristics such as gender and age of household head, physical elevation and slope of household geographical location. S represents exposure to shock indicators such as climate, production, and other (e.g., theft, death), as reported by the households during the endline period. Finally, ζ indicates an idiosyncratic error.

2. Calculate squared residuals from the regression in step 1 (ζ_{it}^2) and run an OLS regression with ζ_{it}^2 as the dependent variable with the same explanatory variables.

$$\zeta_{it}^2 = \sum_{k=1}^{4} \beta_k W_{i,t-1}^k + \sigma X_{it} + \tau S_{it} + \epsilon_{it}$$

3. Use the estimated condition mean (step one), variance (step two), and gamma distribution assumption to calculate household-level conditional probability density function of well-being.

4. Resilience score (ρ_i) is the inverse cumulative probability above the welfare thresh-

old (the average income level in the control group during the endline), given the values of other covariates.

$$\rho_i \equiv \Pr(W_i, t+s \geq \underline{W} | W_{it}, X_{it}, S_{it}) = F(\underline{W}, X_{it}, S_{it})$$

The resilience score falls between 0 and 1 as it reflects the conditional probability of having an acceptable level of well-being during a period.

B.1.3 Subjective Indicators

The subjective indicator of resilience is measured following Jones and d'Errico (2019). We asked respondents nine resilience-related capacity questions (B.3) and aggregated scores to measure household-level resilience capacity. We normalized the score between 0 to 1. A higher score indicates better resilience capacity of households.

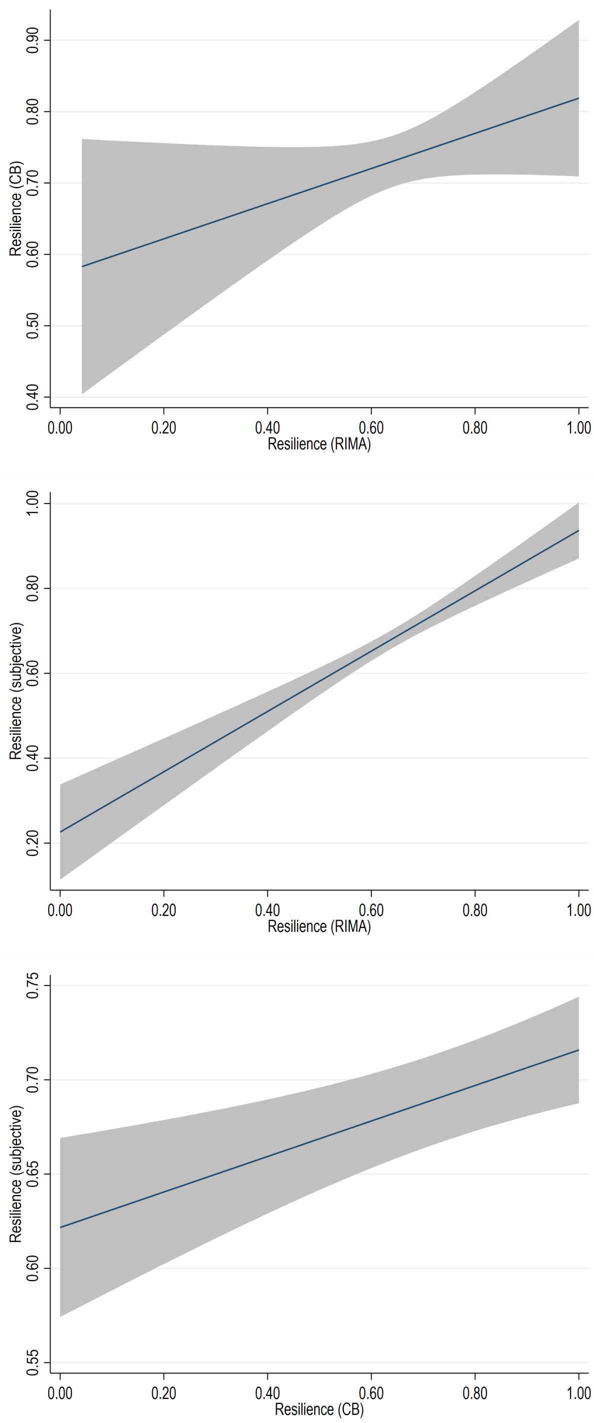

Figure B.1: Resilience indicators

Notes: A linear model fit model is used. 99% confidence interval is shown in the plots.

Table B.2: Variables used to estimate resilience pillars

Indicator	Sub-Index	Pillar
Durable asset	Asset Ownership	ASS
Productive asset	Asset Ownership	ASS
Livestock asset	Asset Ownership	ASS
HH members upto primary education	Human Capital	AC
HH members with secondary education	Human Capital	AC
HH members with graduate education	Human Capital	AC
Dependency ratio	Human Capital	AC
Receive transfers	Safety Nets	SSN
Member of social or economic groups	Safety Nets	SSN
Access to loans	Safety Nets	SSN
Distance to city	Market Access	ABS
Access to safe drinking water	Access to Services	ABS
Access to electricity	Access to Services	ABS
Access to sanitary latrine	Access to Services	ABS

Table B.3: Subjective resilience indicators

Indicator	Description
Q1	Do you agree that your household can bounce back from any challenge that life throws at your household?
Q2	Do you agree that during times of hardship, your household can change its primary income or source of livelihood if needed?
Q3	Do you agree that if threats to your household became more frequent and intense, you would still find a way to get by?
Q4	Do you agree that during times of hardship, your household can access the financial support you need?
Q5	Do you agree that your household can rely on the support of family and friends when you need help?
Q6	Do you agree that your household can rely on the support of politicians and the government when you need help?
Q7	Do you agree that your household has learned important lessons from past hardships that will help you better prepare for future threats?
Q8	Do you agree that your household is fully prepared for any future natural disasters that may occur in your area?
Q9	Do you agree that your household receives useful information warning you about future risks in advance?

C Multiple Hypothesis Testing

We use the false discovery rate (q-values) to adjust for the multiple hypothesis testing and generate sharpened two-stage q-values proposed by Benjamini et al. (2006). Under this exercise, a hypothesis test with a p-value of 0.05 and a q-value of 0.10 implies that rejected null hypotheses with p-values of 0.05 or less (i.e., significant tests) have 10% true nulls (i.e., false positives). We show that the significance levels of our impact estimates do not change after adjusting for the multiple hypothesis testing (Appendix Table B.4 and B.5), which confirms that our significant results across different indicators do not occur by chance.

Table B.4: Multiple hypothesis check

	(1) Coeff	(2) p-value	(3) q-value
Farming practices			
Soil fertility improvment practices	-0.180	0.019	0.006
Soil erosion reduction practices	0.210	0.000	0.001
Crop residue burned in the field	-0.050	0.004	0.002
Planted legumes between seasons	0.040	0.084	0.020
Trees or shrubs along the parcels	0.020	0.135	0.027
Green house on any parcels	-0.020	0.049	0.012
Livestock practices			
Have practiced stall feeding	0.230	0.000	0.001
Use animal waste to produce manure	-0.060	0.000	0.001
Have a rotational grazing plan	-0.110	0.000	0.001
Adaptation index	0.140	0.000	0.001
Income, asset, and resilience			
Household income	189.320	0.002	0.001
Productive	0.130	0.000	0.001
Household	-0.280	0.000	0.001
Livestock	0.120	0.004	0.002
Resilience (RIMA)	0.100	0.000	0.001
Resilience (CB)	0.230	0.000	0.001
Resilience (subjective)	0.110	0.000	0.001

Notes: Multiple hypothesis tests are implemented using the code of Anderson (2008). Variables definitions are available in Appendix B.

Table B.5: Multiple hypothesis

	(1) Coeff	(2) p-value	(3) q-value
Access to training and inputs			
Total no. of benefits received	0.940	0.000	0.001
Information and training	1.040	0.000	0.001
Agriculture inputs	-0.140	0.002	0.001
Livestock inputs	-0.040	0.305	0.051
Forestry inputs	-0.020	0.220	0.041
Organic fertilizer inputs	-0.080	0.000	0.001
Renewable energy inputs	0.060	0.001	0.001
Social capital			
Household still has a LAPA member	0.700	0.000	0.001
Economic	0.300	0.000	0.001
Other	0.360	0.000	0.001
No. of men in different groups	0.310	0.000	0.001
No. of women in different groups	0.410	0.000	0.001
Access to finance			
Total	-627.610	0.000	0.001
Bank	-102.480	0.095	0.022
NGO/MFI	-543.250	0.000	0.001
Cooperative	209.320	0.000	0.001
Informal	-199.030	0.003	0.002
Revenue			
Farming	92.830	0.000	0.001
Livestock	90.860	0.000	0.001
Enterprise	6.930	0.000	0.001
Asset and production loss			
Asset	-0.190	0.000	0.001
Production	0.310	0.000	0.001
Livestock	-0.120	0.000	0.001
All types	0.000	0.985	0.117
Market access			
Any	0.200	0.000	0.001
Crop	0.090	0.000	0.001
Livestock	0.140	0.000	0.001
Enterprise	-0.030	0.033	0.008

Notes: Multiple hypothesis tests are implemented using the code of Anderson (2008). Variables definitions are available in Appendix B.

D Randomization Inference

Randomization inference is a statistical technique that tests the significance of treatment estimates by considering the variations in data resulting from the randomization process. The procedure preserves the original treatment assignments and generates placebo treatment assignments. The impact estimates (i.e., placebo effects) are then estimated with the placebo treatment assignments. The key idea of RI is to compare the estimated treatment effect with the generated placebo effects. Finally, the p-value is calculated, indicating the proportion of times the placebo treatment effects are larger than the estimated treatment effect. For example, an impact estimate of 0.75 with a RI p-value of .05 implies that 5% of all random assignments (i.e., placebo effects) produce an estimate of 0.75 or more.

Table B.6: Randomization inference

	(1) Coeff	(2) ANCOVA (p-value)	(3) RI (P-value)
Farming practices			
Soil fertility improvment practices	-0.18	0.019	0.010
Soil erosion reduction practices	0.21	0.000	0.317
Crop residue burned in the field	-0.05	0.004	0.998
Planted legumes between seasons	0.04	0.084	0.323
Trees or shrubs along the parcels	0.02	0.135	0.027
Green house on any parcels	-0.02	0.049	0.694
Livestock practices			
Have practiced stall feeding	0.23	0.000	0.173
Use animal waste to produce manure	-0.06	0.000	0.092
Have a rotational grazing plan	-0.11	0.000	0.066
Adaptation index	0.14	0.000	0.000
Income, asset, and resilience			
Household income	189.32	0.002	0.328
Productive	0.13	0.000	0.766
Durable	-0.28	0.000	0.572
Livestock	0.12	0.004	0.869
Resilience (RIMA)	0.10	0.000	0.025
Resilience (CB)	0.23	0.000	0.007
Resilience (subjective)	0.11	0.000	0.003

Notes: Randomization interference (RI) tests are implemented using the code of Heß (2017). Variables definitions are available in Appendix B.

Table B.7: Randomization inference

	(1) Coeff	(2) ANCOVA (p-value)	(3) RI (P-value)
Access to training and inputs			
Total no. of benefits received	0.94	0.000	0.000
Information and training	1.04	0.000	0.005
Agriculture inputs	-0.14	0.002	0.929
Livestock inputs	-0.04	0.305	0.637
Forestry inputs	-0.02	0.220	0.006
Organic fertilizer inputs	-0.08	0.000	0.192
Renewable energy inputs	0.06	0.001	0.000
Social capital			
Household still has a LAPA member	0.70	0.000	0.000
Economic	0.30	0.000	0.614
Other	0.36	0.000	0.000
No. of men in different groups	0.31	0.000	0.397
No. of women in different groups	0.41	0.000	0.771
Access to finance			
Total	-627.61	0.000	0.269
Bank	-102.48	0.095	0.311
NGO/MFI	-543.25	0.000	0.098
Cooperative	209.32	0.000	0.309
Informal	-199.03	0.003	0.006
Revenue			
Farming	92.83	0.000	0.653
Livestock	90.86	0.000	0.507
Enterprise	6.93	0.000	0.013
Asset and production loss			
Household asset	-0.19	0.000	0.683
Production	0.32	0.000	0.409
Livestock asset	-0.13	0.000	0.311
All types	0.00	0.985	0.815
Market access			
Any	0.20	0.000	0.085
Crop	0.09	0.000	0.648
Livestock	0.14	0.000	0.030
Enterprise	-0.03	0.033	0.111

Notes: Randomization interference (RI) tests are implemented using the code of Heß (2017). Variables definitions are available in Appendix B.