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LEARNING-ORIENTED REAL-TIME IMPACT ASSESSMENT (LORTA)

Impact evaluation baseline report for FP069:

ENHANCING ADAPTIVE CAPACITIES OF COASTAL COMMUNITIES, ESPECIALLY WOMEN, TO COPE WITH CLIMATE CHANGE INDUCED SALINITY

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PREFACE

In 2018, the Independent Evaluation Unit initiated the Learning-Oriented Real-Time Impact Assessment (LORTA) Programme, within which it collaborates with the Center for Evaluation and Development (C4ED), project teams funded by the Green Climate Fund (GCF), local evaluation teams and academics. The LORTA Programme provides capacity-building and incorporates state-of-the-art approaches for impact evaluations to measure results and learn about the effectiveness and efficiency of GCF-funded projects.

The project "Enhancing adaptive capacities of coastal communities, especially women, to cope with climate change induced salinity", implemented by the United Nations Development Programme in Bangladesh, became part of the LORTA Programme in 2019. The project's overall goal is to strengthen the adaptive capacities of selected Bangladesh coastal communities against the impacts of climate change through the adoption of climate-resilient livelihoods and an increase in drinking water availability. The target population is mainly women who are vulnerable to climate change induced salinity in two districts in the coastal area of southern Bangladesh.

The impact evaluation, based on a clustered, phase-in, randomized control trial design, will shed light on the causal effects of the adoption of climate-resilient livelihoods on beneficiary welfare. This baseline report provides insights about the socioeconomic situation of project households before project implementation.

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FOREWORD

This document is the baseline report for the impact evaluation of project FP069, "Enhancing adaptive capacities of coastal communities, especially women, to cope with climate change induced salinity", in Bangladesh. The project was selected in 2019 to be part of a series of impact evaluations conducted under the Learning-Oriented Real-Time Impact Assessment Programme. The accredited entity for this project is the United Nations Development Programme; implementing partners are the Ministry of Women and Children Affairs (Bangladesh) and the Department of Public Health Engineering (Bangladesh). This project's overall goal is to strengthen the adaptive capacities of selected Bangladesh coastal communities against the impacts of climate change through the adoption of climate-resilient livelihoods and an increase in drinking water availability. The target population is mainly women who are vulnerable to climate change induced salinity in two districts, Khulna and Satkhira, in the coastal area of southern Bangladesh. The impact evaluation will shed light on whether the programme increases the capacity of its beneficiaries to adapt to climate change.

The baseline report is completed before the collection of the endline data and serves as a reference for the estimation of impacts and the interpretation of the impact evaluation findings. It outlines the hypotheses to be tested and the methodological approach and estimation quality checks that will be used in the analysis. Moreover, it presents the baseline summary statistics.

ABBREVIATIONS

CBDW	community-based drinking water solutions
CJS	Chaudhuri, Jalan and Suryahadi (2002)
DPHE	Department of Public Health Engineering
DW	drinking water
EQ	evaluation question
EWS	early warning systems
FCS	Food Consumption Score
FGLS	feasible generalized least squares
GCF	Green Climate Fund
HDDS	Household Dietary Diversity Score
HFIAS	Household Food Insecurity Access Scale
HHDW	household-based drinking water solutions
HHI	Hirschman–Herfindahl Index
IE	impact evaluation
ITT	intention to treat
LATE	local average treatment effect
LH	livelihood
LORTA	Learning-Oriented Real-Time Impact Assessment
M&E	monitoring and evaluation
MoWCA	Ministry of Women and Children Affairs
NGO	non-governmental organization
OLS	ordinary least squares
QR	quantile regression
QTE	quantile treatment effect
RCT	randomized control trial
RWHS	rainwater harvesting system
ToC	theory of change
TOT	treatment effect on the treated
UNDP	United Nations Development Programme
UP	union parishad
UQR	unconditional quantile regression
WLG	women livelihood group

EXECUTIVE SUMMARY

The population in Bangladesh, especially in the coastal areas of the southern part of the country, is very vulnerable to climate-related hazards due to the low elevation above sea level. Their vulnerability is predicted to increase due to the persistent warming of the earth, which causes for a continuing sea level rise and an increase in the reoccurrence of natural hazards, such as floods and cyclones (Bhuiyan and Dutta, 2012). Through sea level rises, natural hazards, changes in river discharge and usage of land, saltwater intrudes into freshwater areas. The increased salinity has two major consequences for the vulnerable population: (1) it directly damages crops and freshwater fish stocks, which are not resilient to rising levels of salinity, which then decreases the productivity of agriculture and aquaculture activities; (2) it increases salinity in the groundwater, damages water supply infrastructure, increases the distances to drinking water sources and causes a deterioration of overall drinking water quality.

As a response to past disasters and a preventive measure against future disasters, the United Nations Development Programme in Bangladesh implemented the project "Enhancing adaptive capacities of coastal communities, especially women, to cope with climate change induced salinity", funded by the Green Climate Fund. In 2019, this project was successfully included in the Learning-Oriented Real-Time Impact Assessment Programme, which has been providing capacity-building in impact evaluations and monitoring project activities since then. As the first major evaluation step, the Learning-Oriented Real-Time Impact Assessment Programme and the United Nations Development Programme teams have collected census and baseline data, conducted baseline analysis and completed the baseline report on the project's beneficiaries. The key components subject to this impact evaluation are climate-resilient livelihoods (Component 1) and drinking water solutions (Component 2).

The impact evaluation employs an experimental design: a randomized control trial with randomization being implemented at the union parishad level in 2021. This impact evaluation aims to answer the following evaluation questions:

1. Do the adaptive livelihoods promoted by the programme provide a sustainable means of earnings for the beneficiaries?
2. Do the drinking water solutions provided by the programme allow beneficiaries to engage in income-generating activities?

We are planning to answer these questions by collecting and analysing the following baseline and endline indicators: household income and expenditure; revenues from income-generating activities, in particular, adaptive livelihoods; household income stability; asset ownership, used to estimate an index that proxies for household wealth; household dietary diversity; food consumption; food secure access; time allocation to various household chores (in particular, collecting drinking water); and household resilience to shocks.

Additionally, we are planning to supplement the impact evaluation with two monitoring questions:

1. What drinking water solution is the most cost-effective?
2. What adaptive livelihood has the largest impact on vulnerability to poverty and on income stability?

The monitoring questions will be addressed by using the project's cost and monitoring data.

At baseline, we collected data from 3,120 households along the southern coastal areas of Bangladesh from 39 union parishads. The basic descriptive statistics showed that:

- The monthly household income amounted to USD 106.84 (equivalent to 9,089 Bangladesh taka [BDT]).

- The income source with the largest absolute amount of income generated in the 12 months before data collection was non-agricultural wage employment (BDT 50,874 for treatment households; BDT 39,652 for comparison households), in which 54.2 per cent (53.6 per cent) of treatment (comparison) households engaged.
- Of female respondents, 77.8 per cent (77.4 per cent of comparison households) had engaged in at least one income-generating activity in the 12 months before data collection. The most common activity women engaged in was livestock production (e.g. cow, goat and sheep, chicken, and duck).
- A female respondent, on average, would decide on how to spend half of the income she was involved in generating.
- At least one climate-adaptive livelihood was already practised in 81.1 per cent (79.9 per cent) of treatment (comparison) households; 66.4 per cent (65.1 per cent) of these cases encompassed a livelihood promoted by the project.
- The average food consumption score of treatment (comparison) households lay at 53.41 (52.51), which was slightly above the threshold for acceptable high food consumption but lower than the national average according to the Bangladesh Integrated Household Survey in 2015.
- Twenty-seven per cent (25.9 per cent) of treatment (comparison) households were considered food secure, 44.8 per cent (37 per cent) mildly food insecure, 23.6 per cent (28.6 per cent) moderately food insecure and 4.6 per cent (8.6 per cent) severely food insecure using the Household Food Insecurity Access Scale categories.
- The water source of 89.9 per cent (87.9 per cent) of treatment (comparison) households was based outside the compound. On average, household members spent a total of 5.5 hours per week on fetching water, which is a female-dominated task. In 77.6 per cent (74.2 per cent) of treatment (comparison) households, only female members were involved in fetching water.
- Respondents from 64.8 per cent (58.4 per cent) of treatment (comparison) households indicated that at least one household member had been affected by a waterborne disease in the 12 months prior to the data collection; this pointed to the need for access to cleaner drinking water.

Overall, the descriptive evidence from the baseline data tends to confirm the suitability of the project activities to the situation and the needs of the target population. In addition, the balance tests – to check whether treatment and comparison households are different in a systematic way – show statistically significant imbalances between the two groups in only a few characteristics. This is expected to happen by chance, especially when balance tests are carried out on a large number of covariates. These imbalances do not mechanically invalidate the experimental design, nor do they systematically warrant adjusting the analysis. Imbalances only matter for covariates that are prognostic of the outcome variable and can be controlled for.

Overall, the groups can be considered similar (on average) prior to project implementation in almost all assessed characteristics. This indicates that the randomization was most likely successful, thereby strengthening the validity of the research strategy that will be used to identify project impacts by comparing the two groups.

I. INTRODUCTION AND CONTEXT

Impact evaluations (IEs) have two main benefits: (1) they increase transparency by measuring the effect of investments; (2) they encourage more effective design and implementation of development projects.

The introductory section of this report gives insights into the set-up of the Learning-Oriented Real-Time Impact Assessment (LORTA) Programme and introduces the reader to the broad country and project context. Details on the project are presented in chapter II. Chapter III presents the theory of change; the evaluation questions follow in chapter IV. In chapter V, we elaborate on the IE design, with details on the timeline, the design itself and the sampling strategy. The identification of causal impacts is discussed in chapter VI, with a presentation of the main effects, heterogeneous effects (i.e. subgroup treatment effects and their differences), and assumptions and limitations. The empirical estimation strategy is presented in chapter VII, with further details on the data to be used, the estimation of average treatment effects and adjusted effects, and the planned robustness checks. Chapter VIII presents summary statistics at baseline, and chapter IX addresses ethical considerations.

A. THE LORTA PROGRAMME

The Independent Evaluation Unit of the Green Climate Fund (GCF) started the LORTA Programme in recognition of the importance IEs have gained in recent years in the development sector and policy analysis. The LORTA Programme keeps track of GCF projects in terms of performance and results and enhances learning within the GCF.

The purpose of the IE is to measure the change in key results areas attributed to GCF project activities. The objectives of the LORTA Programme include:

- Measuring the overall change (outcome or impact) of the GCF's funded projects and enhancing learning
- Understanding and measuring results in different parts of theories of change
- Measuring the GCF's overall contribution to catalysing a paradigm shift and achieving impacts at scale

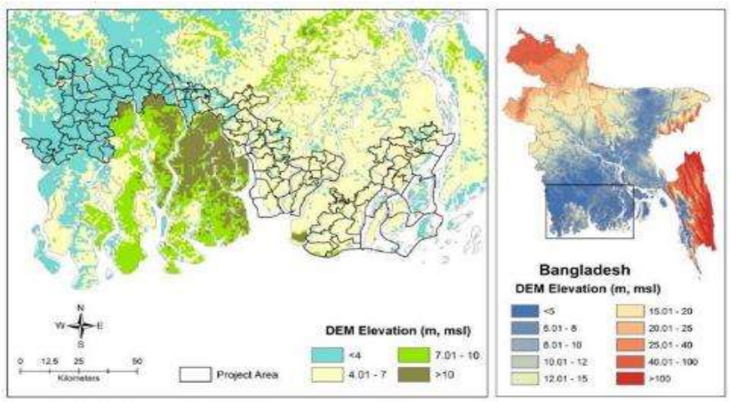
Currently, the LORTA Programme consists of three phases. In the first phase, the goal is to build high-quality, theory-based IE designs at inception. The second phase is the main impact assessment stage, and the third phase involves analysing impact by using baseline and endline data, discussing results and engaging with diverse stakeholders to share results and incorporate feedback as required.

One of the projects initiated in 2019, and currently in the second phase, is "Enhancing adaptive capacities of coastal communities, especially women, to cope with climate change induced salinity" in Bangladesh.

B. COUNTRY AND PROJECT CONTEXT

Bangladesh is a low-income country with a high population density, particularly in the coastal regions. Most of the country's elevation is less than 10 m above sea level, with especially low elevations in the southern part of the country (see Figure 1).

Figure 1. Elevation levels of Bangladesh



Source: UNDP (2018).

Therefore, the population in these areas is very vulnerable to climate-related hazards such as river flooding, cyclones, storm surges and sea level rise. Sixty-one cyclones hit Bangladesh between 1961 and 2013, of which 28 per cent majorly affected the south-western zone (Quadir and Iqbal, 2008), with storm surges ranging from 1.5 to 10 m (Brammer, 2014). Bangladesh has experienced far more than the average observed trends of sea level rise (<4 mm/year), with an observed sea level rise of 6–21 mm/year along the coast of Bangladesh (Climate Change Cell, 2016). Given the ongoing global warming, Bangladesh is likely to face a further sea level rise of up to 88 cm by 2100 (Government of Bangladesh, 2005).

Sea level rises, changes in river discharge and land usage lead to increased sea water intrusion into freshwater areas. The increased salinity has two major consequences for the vulnerable population: (1) it directly damages crops and freshwater fish stocks, which are not resilient to these levels of salinity, which then decreases the productivity of agriculture and aquaculture activities; (2) it increases salinity in the groundwater, damages water supply infrastructure, increases the distances to drinking water (DW) sources and causes a deterioration of overall DW quality. These impacts lead to a loss of income, a loss of agricultural livelihoods (LHs), and growing DW insecurity associated with adverse health impacts. Women and girls are more affected by these impacts. Studies show that women are more likely than men to have adverse health impacts (e.g. hypertension) due to salinity (Nahian and others, 2018). Moreover, high salinity in DW can be associated with pre-eclampsia and gestational hypertension during pregnancy (Khan and others, 2011; Khan and others, 2014). From an economical point of view, traditional gender roles, which are especially present in rural areas of Bangladesh, lead to lower access to formal employment for women (Ahmed and Sen, 2018). Aside from care work, women mainly engage in agriculture- and livestock-related activities (UN Women and BCAS, 2014). Therefore, owing to a lack of alternative income sources, women's options to generate income are disproportionately affected by the loss of productive agricultural land. In addition, men are forced to migrate to engage in more profitable non-farming activities when agricultural productivity is reduced or becomes less lucrative, which increases the vulnerability of their families.

II. THE PROJECT

A. THE INTERVENTION

The project “Enhancing adaptive capacities of coastal communities, especially women, to cope with climate change induced salinity” was implemented in 2019 by the United Nations Development Programme (UNDP) in Bangladesh and was funded by the GCF. This project’s overall goal is to strengthen the adaptive capacities of selected Bangladesh coastal communities against the impacts of climate change through the adoption of climate-resilient LHs and an increase in DW availability. The target population is mainly women who are vulnerable to climate change induced salinity in two districts in the coastal area of southern Bangladesh.

The project consists of three interlinked components, of which components 1 and 2 are most relevant for the IE:

- Component 1 – Climate-resilient LHs
  - Enterprise- and community-based implementation of climate-resilient LHs for women
  - Strengthened climate-resilient value chains and market links for adaptive, resilient LHs
  - Community-based monitoring and last-mile dissemination of early warnings for climate risk informed, adaptive management of resilient LHs
- Component 2 – DW solutions
  - Participatory, site-specific mapping, beneficiary selection, and mobilization of community-based management structures for climate-resilient DW solutions
  - Implementation of climate-resilient DW solutions (at household, community and institutional scales)
  - Community-based and climate risk informed operation, maintenance and management of the resilient DW solutions
- Component 3 – Strengthening of institutional capacity, knowledge and learning
  - Strengthening of the technical and coordination capacities of the implementing partners (the Ministry of Women and Children Affairs [MoWCA] and the Department of Public Health Engineering [DPHE])
  - Establishment of knowledge management, learning, and monitoring and evaluation (M&E) mechanisms

The IE focuses on the first and second components. The third component – aimed at the strengthening of institutional capacity, knowledge and learning – is an overarching component that will affect households in a way not controllable by the IE. Hence, it has been excluded from the IE. Within components 1 and 2, the following activities are the most relevant (as decided through numerous discussions between the LORTA and UNDP teams): adaptive LH activities, early warning systems (EWS) and DW solutions. The goal is to promote synergistic co-benefits between the different activities. Therefore, everyone in a treatment ward will benefit from the DW solutions and EWS, while only some beneficiaries will receive adaptive LH activities. The three types of activity are described in more detail below.

Adaptive LH activities

Women livelihood groups (WLGs) of approximately 25 women, for a total of 1,017 WLGs, will be formed or reactivated. Each WLG will jointly select three out of eight LH options, according to their preferences, for which they will be trained as a group.[1] After completion of the training, they will be asked to select two out of the three trained LHs, for which they will receive the necessary input. The eight LH options were selected with the goal of being appropriate for women's engagement and empowerment as well as suitable for local market conditions. There are three production cycles: for the first cycle, in-kind support of the necessary inputs will be received; for the second cycle, a cash transfer from the Government of Bangladesh (around BDT 20,000 [USD 235] per beneficiary) will be received; for the third cycle, loans can be taken up by a microfinance institution to slowly phase in financial independence.

EWS

To equip the target group with the capacity to undertake adaptive planning and management of the new climate-resilient LHs, it necessary to raise awareness and understanding of climate risk reduction strategies. First, the project will work with local authorities to tailor messages from existing EWS to the needs of local populations. Complex meteorological data will be summarized and provided, along with clear information on the potential consequences of upcoming weather events, complemented by clear instructions on how people should react and protect themselves. Second, women early warning volunteers, who will be part of the WLGs, will be trained in the selected wards in coordination with the Cyclone Preparedness Program and with disaster management committees at the union parishad (UP) level. These activities aim to improve EWS dissemination and gender-responsive messaging.

DW solutions

The DW solutions consist mainly of constructing rainwater harvesting systems (RWHS), ensuring water supply during the dry season.[2] The use is exclusively directed at DW, not at water resources for agriculture, cooking or personal hygiene. This activity is the largest part of the project in terms of budget and includes the development of new and innovative technology for RWHS.

The RWHS can be installed in appropriate sizes at the household level, community level or institutional level. The capacity of a household-level water tank is 2,000 L. DW solutions are also delivered by other partners in the target area, but these differ from the ones offered in this project. The plan is to install 13,308 RWHS at the household level, for which a small co-financing is required (this could also be contributed in-kind by helping to build the RWHS); 228 RWHS at the community level, each covering approximately 25–50 households (e.g. at mosques, temples or other community buildings); 19 RWHS at the institutional level, each covering approximately 75–100 households (e.g. at schools or other government institutions); and 41 pond embankments and filtration systems. At least 20 per cent of target households in each ward should receive a household-level RWHS.

Water user groups and water management committees will be formed to ensure sustainable planning and maintenance of the water solutions. The water user groups will consist of women of targeted households. They will receive training at workshops and will be responsible for smaller maintenance tasks and daily or monthly maintenance; bigger maintenance operations will be taken care of by a technician from the water management committee at the ward level. Further backstopping will be done by the DPHE. A small fee will be charged annually for basic maintenance and operation, varying per level. Beneficiaries of household-level RWHS will be additionally encouraged to set an amount aside for further repairs.

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[1] The eight livelihood options are crab fattening, crab nursery, crab and fish feed processing, homestead gardening, aqua-geoponics, hydroponics, sesame cultivation, and plant nursery.
[2] The dry season in Bangladesh lasts from November until February. The climate is characterized by a short spring – from March to May – and a long season of rains, which runs from June to October.

B. PROJECT BENEFICIARIES

An estimated 719,229 people will, directly and indirectly, benefit from the project intervention according to the project's documentation. This equals around 16.25 per cent of the total population in the two districts.

In total, 245,516 direct beneficiaries (around 50 per cent female) will be targeted by the project. All beneficiaries will be reached by the EWS component; the LH component is targeted at 25,425 selected beneficiaries, all female; and the DW component is targeted at 136,100 beneficiaries, of which 50 per cent will be female. The direct beneficiaries were chosen based on their need for support, as identified from a census conducted in early 2021. Nearby communities in the targeted wards are expected to benefit indirectly from the project through knowledge-sharing and learning mechanisms. The number of indirect beneficiaries amounts to 473,713.

The project particularly targets female participants as it is often women's responsibility to provide the family with safe DW. The large amount of time spent on fetching water reduces the time available for domestic chores, reduces women's opportunities to engage in economic activities and increases safety issues due to travelling long distances (Camey and others, 2020; Sommer and others, 2015). Additionally, Pregnant women and children are also more vulnerable to, and face worse consequences from, adverse health effects originating from unsafe DW.

For the estimation of project impacts on selected beneficiaries, a comparison group was constructed through the development of a clustered phase-in design (see section V.A.2).

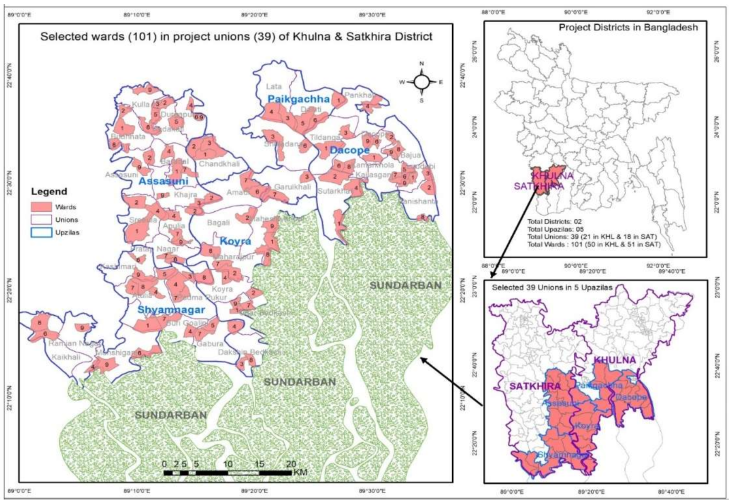
C. GEOGRAPHICAL SCOPE

The project will be implemented in the two districts of Khulna and Satkhira. Within the districts, 39 UPs were selected (18 in Satkhira and 21 in Khulna) across five *upazilas*[3] (Assasuni, Koyra and Shyamnagar in Satkhira district; Dacope and Paikgachha in Khulna district). Within the selected UPs, 101 out of 350 wards were selected (see Figure 2). The 39 UPs were selected based on their exposure to salinity, including projected salinization, and prevalence of extreme poverty; the 101 wards were selected based on current and projected salinity level (based on maps of soil salinity), a poverty index (based on income poverty, percentage of day labourers and satellite imagery analysis of housing structures) as well as high exposure to salinity intrusion due to low elevation levels.[4]

[3] The upazilas are the second-lowest tier of regional administration in Bangladesh. The administrative structure consists of divisions (8), districts (64), upazilas and UPs.

[4] The selection of project areas was carried out by the project team at UNDP Bangladesh.

Figure 2. Project location map



Source: UNDP (2018).

D. RELEVANT GOVERNMENT STRATEGIES LINKED TO THE PROJECT

The Government of Bangladesh commits to tackling climate change in the context of its overall country development through several frameworks.

The Government emphasizes its planned actions to tackle climate change as part of its Seventh[5] and Eighth[6] Five Year Plans, setting the stage for the country's development during these periods (General Economics Division, 2015; General Economics Division, 2020). Moreover, in its nationally determined contributions (Government of Bangladesh, 2020), submitted first in 2015 and adjusted in 2020, the Government emphasizes that addressing climate change by promoting climate-resilient LHs, water security and EWS, among other measures, is one of the country's main priorities now and in the upcoming years.

A more concrete framework for the country's climate change action plans was put together in the Bangladesh Climate Change Strategy and Action Plan. Additionally, the Climate Change and Gender Action Plan puts the focus on ensuring gender equality in climate change related policies and manifests the country's commitment to this.

Some of the initiatives already undertaken by the Government are:

- Coastal Embankment Improvement Project (2002–2013): support for agricultural production by reducing saltwater intrusion into polders
- Southwest Area Integrated Water Resources Planning and Management (Asian Development Bank): support for flood control, drainage and irrigation schemes
- Emergency 2027 Cyclone Recovery and Restoration Project (2013–today): support for restoration and recovery from damage to infrastructure and LHs caused by Cyclone Sidr
- The Humanitarian Preparedness and Response (UK Department for International

[5] Covering the years 2016–2020.
[6] Covering the years 2021–2025.

Development): risk and disaster management

- Comprehensive Disaster Management Programme: adaptation interventions and EWS
- Rural Water Supply and Sanitation Project: provision of safe DW and sanitation
- Bangladesh Pilot Programme for Climate Resilience: support for climate-smart technologies

Despite all these efforts, many climate change related impacts, particularly the vulnerability of women related to climate change, have not actively been focused on.

The project presented in this report was designed to support the Government of Bangladesh in achieving its targets and visions related to climate change adaptation by strengthening the adaptive capacities of coastal communities to cope with the impacts of climate change induced salinity on their LHs and water security; the project is intended to empower communities, especially women. This project aims to move away from short-term and technology-led interventions and instead focuses on a community-centred approach, creating sustainability by fostering ownership and building capacity within local communities.

E. MAIN IMPLEMENTING AGENCIES AND STAKEHOLDER INVOLVEMENT

The main local implementing agency is the MoWCA, which is responsible for the overall management of the project, in coordination with UNDP, which is responsible for quality assurance. The implementation will follow the UNDP's national implementation modality.

The MoWCA is supported by other local governmental agencies. The Department of Women Affairs will assist in achieving the targets under Component 1 (and 3), while the DPHE will support the implementation of activities under Component 2.

Field-level implementation will be led by the respective local government divisions. The UP staff and the Women Standing Committee will be involved in the implementation of Component 1, while the water management committees and UP-level Women Standing Committees will assist in the implementation of Component 2.

The in-field activities will be delivered by three local non-governmental organizations (NGOs): the Bangladesh Rural Advancement Committee, the Center for Natural Resource Studies and Dushtha Shasthya Kendra. Each NGO will be responsible for the implementation of activities in a different implementation area that was randomly assigned to the NGO as part of the evaluation (see section V.A.3). The work of the NGOs will be directly supervised by the local government divisions. Additionally, the Department of Women Affairs and the DPHE will provide technical assistance and monitor the activities relevant to their respective responsibilities.

The project was set up with a focus on stakeholder involvement throughout all project stages (i.e. the design and the various implementation stages). State and non-State actors, including local communities, ethnic minorities, NGOs, academics, local government institutions, relevant government ministries, civil society organizations and donors, were consulted at the proposal stage to ensure the appropriateness of the proposed project design. During the official project approval process, various governmental stakeholders were consulted; finally, the project was aligned with other projects being implemented by the MoWCA. This stakeholder consultation process will continue during all stages of implementation to ensure stakeholder involvement and participation.

F. IMPLEMENTATION PROGRESS

The project has a total timespan of 5 years, from 2019 to 2024. Table 1~~Table 1~~ gives an overview of completed or soon-to-be-implemented project-related activities. During the first year of the project, village and community-specific mapping and participatory planning were conducted. Owing to the COVID-19 situation in Bangladesh as well as several natural disasters (e.g. Cyclone Amphan in May 2020), this stage of the project took longer than expected and was finalized in November 2020.

From December 2020 to January 2021, in the second year of the project and prior to the implementation of project activities, a full household census was carried out in the project districts to gather the information required to compute the household vulnerability scores that determine eligibility for treatment. The census data collection included 66,171 households and was used to randomly select a baseline sample for in-depth structured interviews, which includes 3,120 households eligible for the project. The baseline data were collected in September and October 2021. Until the endline data collection,[7] the focus will be on monitoring, which helps inform the IE.

WLG formation and ward-level LH profiling were completed and built the basis for the implementation of the LH component. In November 2021, training of trainers on adaptive LHs was started in the project UPs. Participants in the training of trainers will then be responsible for delivering training to WLGs. After training is completed, each WLG will receive input support for two out of the three LH options they were trained on. Input support will last for three production cycles and hence will last between 12 and 18 months, depending on the type of LH.[8] At the central level, a training of trainers workshop for MoWCA staff on the gender–climate nexus was held in December 2021.

Additionally, the implementation of DW-related activities was initiated. Seven community- and institution-based RWHS were installed in six UPs, functioning as a pilot, prior to expanding the installation to the outstanding UPs. Consultation meetings on fee-based modelling of community-, institution- or pond-based RWHS installations were completed in December 2021. Water quality testing took place thereafter.

Table 1. Overview of implementation and M&E activities

COMPONENT	ACTIVITY	STATUS IN TREATMENT AREAS	STATUS IN COMPARISON AREAS
LH	WLG formation	Completed	Completed
LH	Ward-level LH profiling	Completed	Completed
LH	Training of trainers on adaptive LHs	Completed	Planned for summer 2022
LH	Gender–climate nexus training of trainers for MoWCA	Central level	Central level
LH	Training on adaptive LHs for beneficiaries	Completed	Planned for October 2022
LH	Input distribution for adaptive LHs for beneficiaries	Completed	Planned for October 2022
DW	Community- and institution-based RWHS installation (pilot)	7 completed	6 UPs

[7]At the time of writing, the evaluation team and UNDP are still in discussions regarding how long the implementation agencies can wait before rolling out adaptation livelihood activities to the households in the comparison group. It is important to find a consensus among the various parties that accounts for the IE's needs while respecting operational constraints and commitments.
[8] Some livelihoods have longer production cycles than others.

Component	Activity	Status in treatment areas	Status in comparison areas
DW	Consultation meeting on fee-based modelling for community-, institution- or pond-based RWHS	Completed	Completed
DW	Water quality testing for HHbRWHS	In process	In process
M&E	Census data collection	Completed	Completed
M&E	Beneficiary selection and verification	Completed	Completed
M&E	Baseline data collection	Completed	Completed
M&E	Development of monitoring system	Completed	Completed
Overall	Village and community-specific mapping, participatory planning	Completed	Completed
Overall	Market actor mapping	Completed	Completed

Abbreviations: DW = drinking water, LH = livelihood, M&E = monitoring and evaluation, MoWCA = Ministry of Women and Children Affairs, RWHS = rainwater harvesting system, HHbRWHS = household-based rainwater harvesting system, UP = union parishad, WLG = women livelihood group.

III. THEORY OF CHANGE

Figure 3~~Figure 3~~ presents the theory of change (ToC) associated with the two types of project activities subject to the IE, namely the LH component and the DW component (see section II.A for more detail). The LORTA and UNDP teams developed the ToC together during the design stage of the evaluation. The ToC displays the needed inputs and activities, which are expected to translate into intended outputs and outcomes. In the longer term, several aspects of the beneficiaries' (and their respective households') lives are intended to be impacted by their project participation.

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In the LH component, financial and human resources are required for the creation or reactivation of WLGs across the project area, with women from beneficiary households as members. The eight adaptive LHs[9] the project focuses on will be promoted to the WLGs, and each WLG will choose three of the LHs to receive training on. After the training, the WLGs will choose two of the LHs for which they will receive input support (USD 160 per household) for three production cycles.[10] The intended outcome is that the project beneficiaries, who have received training and inputs for LHs, will adopt those LHs. In the final stage, this will translate into an impact on the women's income, as well as their decision-making power within the household. Through an increase in women's income, the household income is expected to increase. One intended impact of the project is income stability, and – through income increases – the household food security situation is expected to improve.

In the DW component, financial and human resources – together with construction materials – are needed as input for the implementation of the component, which entails the construction of household and community-based RWHS. The intended outcome of this component is that beneficiary households, after the construction of RWHS, have year-round access to clean DW closer to their houses. This is expected to translate into women, who are mainly responsible for fetching water,[11] spending less time doing so. This, in return, is expected to translate into women having more time to participate in WLGs and adopting adaptive LHs (see II.A).

The LH and DW components are highly interlinked. The assumption that women will adopt the adaptive LHs (assumption 2) is dependent on women having enough time to engage in income-generating activities, which will be directly influenced by the DW component since it aims to reduce women's time spent fetching water. In addition, for women to have sustainable means of earnings, they need to be able to protect their new LHs against extreme weather events, which will only be possible if the EWS subcomponent has been carried out successfully and effectively.

Each link of the causal chain established by the ToC relies on several crucial assumptions, indicated in Figure 3~~Figure 3~~ by numbers or letters (numbers 1–8, letter M), which are used as references when explaining all underlying assumptions.

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The ToC makes the following assumptions:[12]

1. *LH component: inputs to activities*
    a. All needed inputs are available.
2. *LH component: activities to outputs*
    a. All identified beneficiaries belong to a WLG.

[9] The eight livelihood options are crab fattening, crab nursery, crab and fish feed processing, homestead gardening, aqua-geoponics, hydroponics, sesame cultivation, and plant nursery.
[10] For the first cycle, in-kind support of the necessary inputs will be received, for the second cycle a cash transfer will be received from the Government of Bangladesh, and for the third cycle, loans can be taken up by a microfinance institution to slowly phase in financial independence.
[11] In the majority of households included in the baseline sample, solely women are responsible for fetching water (see section VIII.B).
[12] The numbering refers to the numbers displayed in the ToC (Figure 3~~Figure 3~~).

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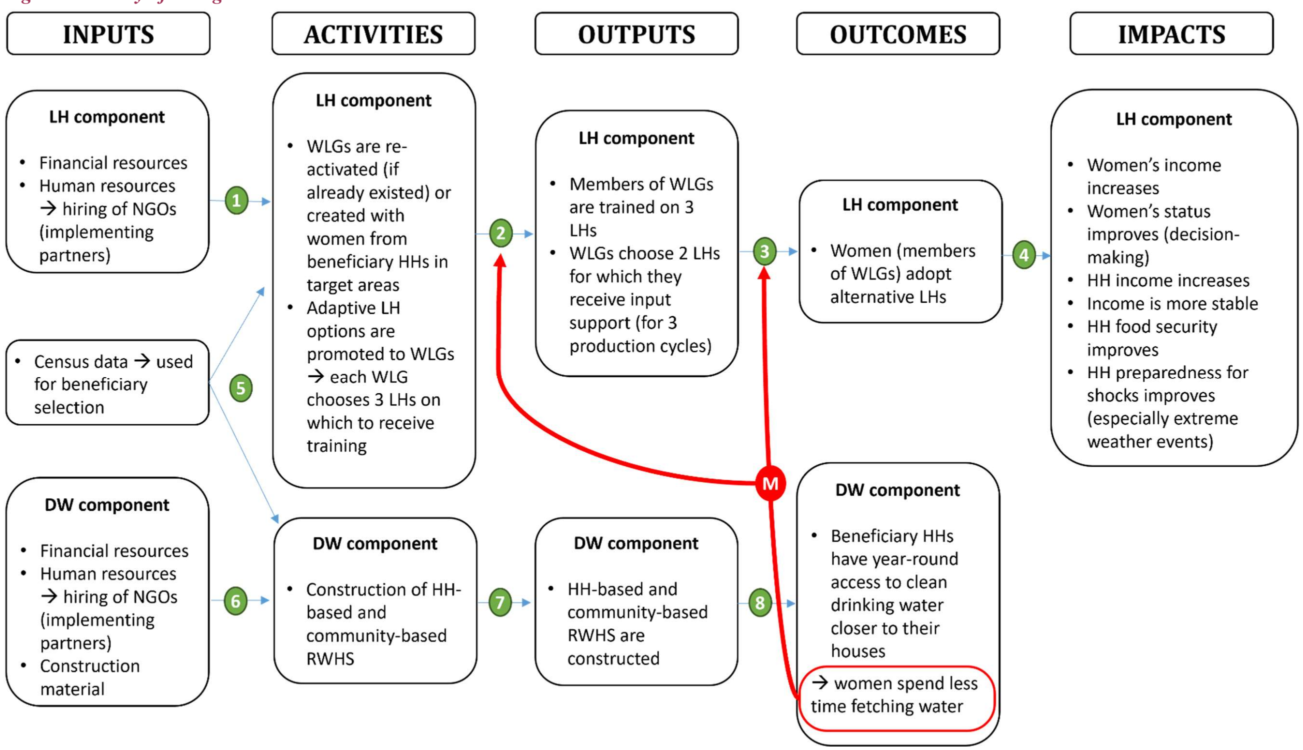
   b. Women in WLGs are motivated, have time to participate in the trainings and are allowed by their partner or families to participate.
   c. WLGs are able to consensually choose three LHs for training.
3. *LH component: outputs to outcomes*
   a. WLGs are able to consensually choose two LHs for input support.
   b. Training and inputs are sufficient to equip women with the necessary knowledge and material to start engaging in adaptive LHs.
   c. Women have the necessary prerequisites to permanently engage in LHs (e.g. time they can dedicate to activity, land ownership and decision-making power).
4. *LH component: outcomes to impacts*
   a. Adaptive LHs are adequate and adapted to context (e.g. resistant to saline soil and weather conditions).
   b. Market links are established so that production from adaptive LHs can meet the demand.
   c. There is sufficient demand to sell the production from adaptive LHs.
   d. Adaptive LHs generate profits.
5. *Census data*
   a. Census data are collected from all households in target areas.
   b. Census data allow eligible households to be correctly identified as per the criteria defined by the project.
6. *DW component: inputs to activities*
   a. All needed inputs are available.
   b. There is adequate knowledge to construct the RWHS.
7. *DW component: activities to outputs*
   a. There is enough material to construct the RWHS.
8. *DW component: outputs to outcomes*
   a. RWHS are operational.
   b. There is enough rain during the rainy season to fill the tanks.
   c. RWHS are solid and can resist extreme weather events.

Mechanism (M)

a. Women reallocate time from fetching water towards training on adaptive LHs.
b. Women reallocate time from fetching water towards income-generating activities, in particular, adaptive LHs promoted by the project.

Figure 3. Theory of change



Notes: LORTA team

Abbreviations: DW = drinking water, HH = household, LH = livelihood, NGO = non-governmental organization, RWHS = rainwater harvesting system, WLG = women livelihood group.

IV. EVALUATION QUESTIONS AND INDICATORS

The ToC (Figure 3~~Figure 3~~) and underlying assumptions (chapter III), as well as project implementation updates, guided the formulation of the evaluation questions (EQs), which will be tested in the endline analysis to inform whether the implementation of the intervention had an impact on the outcomes. The overarching question, which constitutes the starting point of the evaluation, is the following: Does the programme increase the capacity of beneficiaries to adapt to climate change?

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Notwithstanding its intrinsic value, such a question is too broad to be answered directly by an IE. Therefore, we identified – in collaboration with the project team – a set of more precise EQs in line with the project's ToC, relating to the individual impacts of each project component.

In essence, each of the EQs relates to a specific treatment modality of the project. As such, each EQ requires a specific variation in treatment – either in its intensity, timing or components – to allow for identification of the corresponding causal impacts (i.e. for the attribution of measured impacts to the respective treatment modality). Given the contextual circumstances and constraints inherent in project design and implementation, as well as budgetary and timing considerations, it is typically not feasible to accommodate all the required treatment variations within a single IE (i.e. it is not possible to answer all EQs in a satisfactory manner within a single IE). For the DW component, introducing experimental variation was not in line with the component's underlying social ethics given the urgency of the situation.[13] For the EWS component, activities involve a complex collaboration between multiple actors (from the project or not) at multiple levels (ward and UP), and there is no clear potential for experimental variation.[14]

Therefore, and in line with discussions with the project team, the counterfactual impact study will focus on the LH component and the following EQ. Chapter V elaborates on the design of the IE in more detail.

EQ: Do the adaptive LHs promoted by the programme provide sustainable means of earnings?

The IE will seek to answer the EQ by measuring the impact on the following indicators:

Intermediate: Adoption rate of adaptive LHs.

Final:

- Household income and expenditure
- Revenues from income-generating activities, in particular, adaptive LHs
- Household income stability[15]
- Asset ownership, used to estimate an index that proxies for household wealth
- Household Food Consumption Score (FCS)
- Household Food Insecurity Access Scale (HFIAS) developed by INDDEX Project (2018)
- Household resilience to shocks (exposure to natural disasters, consequences of said disasters on household LH, how well the household has recovered, time preferences, attitudes towards risk)

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[13] The project team stated that the issue of drinking water was too pressing and too crucial for the life of people in the project areas to allow randomly not implementing or delaying the implementation of drinking water solutions.
[14] In addition, the scope of the component is somewhat larger than project areas, as some activities take place at the UP level, hence covering both project and non-project wards. This aspect added difficulty in identifying a suitable control group.
[15] For details on measurement, see section VII.D.

Additionally, we formulated the following question relating to the key mechanism targeted by the project to achieve impacts:

M1. Do the DW solutions provided by the programme allow beneficiaries to engage in income-generating activities?

Indicator: Time allocation (trade-off between time spent fetching water and time allocated to income-generating activities).

Finally, UNDP showed a keen interest in learning additional information about the effectiveness and mechanics of the programme:

A1. What DW solution is the most cost-effective?

Indicators: Detailed project cost data.

[Tentative] M&E data on sales, profits and/or income of beneficiaries.

A2. What adaptive LH has the largest impact on vulnerability to poverty and income stability?

Indicators: Detailed project cost data.

[Tentative] M&E data on sales, profits and/or income of beneficiaries.

We list some indicators as tentative because we propose to rely on M&E data to investigate questions A1 and A2, as a complement to the IE. The reason for investigating A1 separately is that answering A1 based on the IE would require causal estimates of the differential impacts of household-based and community-based DW solutions (HHDW and CBDW). As explained in the next section, this will not be part of the IE. Similarly, answering A2 within the IE would require causal estimates of impacts for each one of the eight LH options offered by the programme, whereby each WLG will select the activities for which they wish to receive training and input support. Based on our current knowledge of the implementation plan and discussions with UNDP, there is no feasible IE design to answer A2 directly.

Table 2~~Table 2~~ maps key indicators to the various elements of the IE ToC presented in Figure 3~~Figure 3~~.

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Table 2. Key indicators

ToC	Item	Indicator	Data source
LH component Activities	WLGs are reactivated (if already existed) or created with women from beneficiary households in target areas	No. of WLGs in target areas	MIS
		No. of women who report membership	Survey
	Adaptive LH options are promoted to WLGs → each WLG chooses 3 LHs on which to receive training	No. of WLGs that received information and chose 3 LHs for training	MIS
Assumption 2 & Mechanism M	Women in WLGs are motivated, have time to participate in the trainings and are allowed by their partner or families to participate Women reallocate time from fetching water towards training	No. of beneficiaries who attended and received training	MIS Survey
		Time allocation of women	Survey
		Women's decision-making power in the household	Survey

ToC	Item	Indicator	Data source
LH component Outputs	Members of WLGs are trained on 3 LHs	No. of training sessions delivered	MIS
		Topics covered in training	MIS Survey
	WLGs choose 2 LHs for which they receive input support (for 3 production cycles)	No. of WLGs that receive input support	MIS Survey
		No. of beneficiaries that receive input support	MIS Survey
Assumption 3	Training and inputs are sufficient to equip women with the necessary knowledge and material to start engaging in adaptive LHs	Extent of input support	MIS Survey
LH component Outcomes	Women (members of WLGs) adopt adaptive LHs	No. of beneficiaries who practise adaptive LHs	MIS Survey
		Time allocation of women	Survey
Assumption 4	Adaptive LHs are adequate and adapted to context (e.g. resistant to saline soil and weather conditions)	Type of LH adopted by beneficiaries	MIS Survey
	Adaptive LHs generate profits	Household profits from adaptive LHs	MIS Survey
LH component Impacts	Women's income increases	Women's income generated	Survey
	Women's status improves (decision-making)	Women's decision-making power in the household	Survey
		Women's participation in social life	Survey
		Women's participation in adaptive LHs (self or women only versus joint production with partner or husband)	Survey
	Household income increases	Household income	Survey
		Household expenditures (proxy)	Survey
	Income is more stable	Household income shares	Survey
	Household food security improves	Household Food Consumption Score	Survey
		Household Food Insecurity Access Scale score	Survey
		Household food expenditure	Survey
		Household assets	Survey

ToC	Item	Indicator	Data source
	Household preparedness for shocks improves (especially extreme weather events)	Self-reported preparedness	Survey
DW component Outcomes	Beneficiary households have year-round access to clean DW closer to their houses	No. of beneficiaries who have access to household-based DW solutions	MIS Survey
		No. of beneficiaries who have access to community-based DW solutions	MIS
		No. of households whose members suffered from waterborne disease	Survey
	Women spend less time fetching water	Time allocated by women to fetching water	Survey
Mechanism M	Women reallocate time from fetching water towards income-generating activities, in particular, adaptive LHs promoted by the project	Time allocation of women	Survey

Abbreviations: DW = drinking water, LH = livelihood, MIS = monitoring and information system, ToC = theory of change, WLG = women livelihood group.

V. IMPACT EVALUATION DESIGN

The IE follows an experimental design that will provide robust causal estimates of the impact of the LH component of the project. This chapter details the IE design and the randomization procedure, before turning to the sampling strategy.

A. EVALUATION DESIGN

1. PROGRAMME ACTIVITIES

The programme offers training and input support on eight adaptive LHs. We consider the LH component of the programme as one package. That is, the design does not explicitly take into account the heterogeneity of the various LHs and considers all "bundles" of LHs to be equivalent.[16] In other words, the LH component is considered as one homogeneous treatment modality.

Eligible pool and comparison group[17]

The project decided to select, in priority, the most vulnerable UPs and, within these, the most vulnerable wards. As such, non-project UPs and non-project wards are intrinsically different from project areas. Furthermore, within the selected wards, the project identified specific households as eligible for treatment based on demographic and socioeconomic criteria. An ideal comparison group consists of similarly eligible households within treatment areas to ensure that the comparison households exhibit similar background characteristics to treatment households. Similarly, selecting a comparison group from within treatment areas would alleviate concerns regarding programme placement bias.

We now turn to presenting an IE design that enables the research team to build such a comparison group, which we will refer to as the "control group", given the experimental nature of the design.

2. EXPERIMENTAL DESIGN: CLUSTERED PHASE-IN RANDOMIZED CONTROL TRIAL

The IE follows a clustered phase-in randomized control trial (RCT), where project UPs are the clusters.[18] In this set-up, all eligible households will eventually receive the LH programme activities as planned.[19] The LH intervention will be rolled out in two phases; project activities will be implemented only in the first group during Phase 1 and extended to the second group during Phase 2. The project identified 39 project-eligible UPs; the first group of 25 UPs receive the LH interventions during Phase 1, and the second group of 14 UPs receive them during Phase 2.[20] Activities also continue in the group treated in the previous phase (i.e. the second group will start receiving treatment while

[16] As explained in section II.A, each WLG selects three livelihoods on which to receive training, and after training is completed each group selects two livelihoods for which to receive input support. In essence, this means that the LH component will actually be different for each WLG given that the choice of livelihoods is left to self-selection. We evaluate the LH component as a whole and do not distinguish between the different types of livelihood due to self-selection and the challenges of identifying what is driving it.

[17] Details on the selection of project areas and beneficiaries are given in sections II.B and II.C.

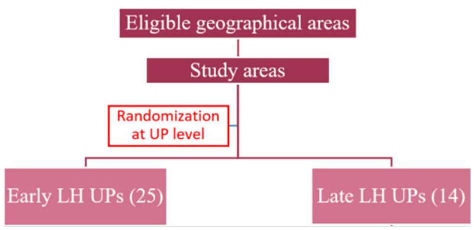
[18] UNDP conveyed that assignment to groups should be made at the UP level, rather than at the ward, village or individual household level. From an operational standpoint, the choice of UPs as the treatment assignment units is expected to increase the capacity of the implementing partners to comply with the experimental design.

[19] Not all wards will be part of the project within a given project UP. The project has already identified project wards within the selected project UPs, and eligible households are identified within said project wards thanks to the project census data.

[20] In principle, a phase-in design could count more phases. The choice of having two groups and keeping a smaller share of target UPs in the control group was made in consultation with UNDP, taking into account UNDP's programmatic and operational commitments.

project activities are continuing for the first group). The roll-out of LH activities will take place in February 2022 in Phase 1 UPs and, tentatively,[21] in March 2023 in Phase 2 UPs. The proposed clustered phase-in design is experimental in nature, as the groups are assigned to each phase **randomly** (see Figure 4~~Figure 4~~).

Figure 4. Clustered phase-in design



Abbreviations: LH = livelihood, UP = union parishad.

With the staggered implementation, beneficiaries in the UPs of Group 2 (the "Late LH" group in Figure 4~~Figure 4~~) constitute the control group for the IE, as summarized in Table 3~~Table 3~~.

Table 3. Phase-in of LH interventions with two groups

PHASE	TREATMENT GROUP	COMPARISON GROUP
1	**Group 1** *No. of UPs: 25* *No. of wards: 65[a]* *Planned no. of LH beneficiaries: 16,340[b]*	**Group 2** *No. of UPs: 14* *No. of wards: 36[a]* *Planned no. of LH beneficiaries: 9,150[b]*
2	**Group 1 + Group 2** *No. of UPs: 39* *No. of wards: 101* *Planned no. of LH beneficiaries: 25,490*	

Source: LORTA, based on preliminary beneficiary lists shared by UNDP in June 2021.
Abbreviations: LH = livelihood, UP = union parishad.
[a] Estimated before randomization based on the average number of wards per UP.
[b] Estimated before randomization based on the average number of LH beneficiaries per UP.

3. RANDOMIZATION PROCEDURE

As presented above, the evaluation team and UNDP agreed on randomization at the UP level, with the following allocation of the 39 identified project UPs: 25 UPs allocated to Phase 1, and 14 UPs allocated to Phase 2. Table 4~~Table 4~~ presents the allocation of Phase 1 and Phase 2 UPs for each NGO (implementing partner):

Table 4. Randomization – Allocation of UPs by NGO

NGO	UPAZILAS COVERED	TOTAL NUMBER OF UPS	NUMBER OF UPS PHASE 1	NUMBER OF UPS PHASE 2
BRAC	Assasuni	10	6	4

[21] UNDP is finalizing the timeline internally.

NGO	Upazilas covered	Total number of UPs	Number of UPs Phase 1	Number of UPs Phase 2
CNRS	Koyra, Shyamnagar	15	10	5
DSK	Dacope, Paikgachha	14	9	5
TOTAL		**39**	**25**	**14**

Source: LORTA, based on project data.
Abbreviations: BRAC = Bangladesh Rural Advancement Committee, CNRS = Center for Natural Resource Studies, DSK = Dushtha Shasthya Kendra, NGO = non-governmental organization, UP = union parishad.

The allocation by NGO presented in Table 4~~Table 4~~ was made arbitrarily[22] by the evaluation team to ensure that each NGO had more UPs to cover during Phase 1 than during Phase 2. In addition, the randomization procedure implemented by the evaluation team accounted for upazila-level stratification. The rationale for stratifying at this level is twofold: (1) it ensures that each upazila includes both Phase 1 and Phase 2 UPs, and (2) given that the catchment areas of the implementing partners are defined by upazila (see Table 4~~Table 4~~), stratification at the upazila level mechanically implies stratification at the NGO level, which in turn mitigates concerns relating to implementer bias.[23] Table 5~~Table 5~~ shows the allocation of Phase 1 and Phase 2 UPs within each upazila.

Table 5. Randomization – allocation of UPs by upazila

NGO	Upazila	Total number of UPs	Number of UPs Phase 1 implementation	Number of UPs Phase 2 implementation
BRAC	Assasuni	10	6	4
DSK	Dacope	9	6	3
CNRS	Koyra	7	5	2
DSK	Paikgachha	5	3	2
CNRS	Shyamnagar	8	5	3
TOTAL		**39**	**25**	**14**

Source: LORTA, based on project data.
Abbreviations: BRAC = Bangladesh Rural Advancement Committee, CNRS = Center for Natural Resource Studies, DSK = Dushtha Shasthya Kendra, NGO = non-governmental organization, UP = union parishad.

The allocation was enforced by implementing the following procedure for each upazila separately:

1. Sort observations based on the UP identification number (variable called "union" in the project census data).
2. For each UP within that upazila, generate a random number in the range [0,1] drawn from a uniform distribution.
3. Sort the UPs based on the value of the random numbers (in ascending order).
4. Repeat Steps 2 and 3 one hundred times.
5. From the resulting random sorting of UPs, assign the first *n* UPs to Phase 1 implementation. For example, in Assasuni, the first six UPs were assigned to Phase 1 and, in Koyra, the first five UPs were assigned to Phase 1.

[22] A random choice was required because the overall allocation ratio (25/14) did not yield round numbers when applied to each NGO, given the low number of UPs.
[23] Implementer bias can arise when several organizations implement a single programme. The source of the bias is that said organizations may implement programme activities in different ways (e.g. according to the culture or experience of the organization implementing that activity). Such a situation begs the question of whether the programme is actually comparable across the various implementing agencies and, hence, whether the estimated impacts may be affected by heterogeneity that actually reflects differences between implementers.

The IE team used the project census data to check the balance across Phase 1 and Phase 2 UPs. As the results in Table 10~~Table 10~~ show (see appendix), there is no statistically significant imbalance for the selected variables. The list of variables used in the analyses, both from census and survey, with measurements are listed in the appendix.

B. Sampling strategy

1. Sample size

The IE team carried out sample size calculations to determine the number of observations required for the study to be able to detect the expected impacts with acceptable statistical precision. Household yearly income was chosen as the key outcome for the calculations. Baseline values for the outcome mean, standard deviation and UP-level intra-cluster correlation[24] were taken from a survey carried out by Practical Action Consulting in 2019 in the project areas. The survey collected information on the households' monthly average income and their primary and secondary sources of income. Because of inconsistencies in the data on secondary income, we only consider primary income for this exercise. Furthermore, the primary income variable exhibits unlikely extreme observations.[25] We trim the bottom 1 per cent of observations and winsorize the variable at 99 per cent, before multiplying it by 12 to get an estimate of yearly household income. We obtain a sample average of BDT 90,530 for a standard deviation of 55,233 and a UP-level intra-cluster correlation of 0.054. In line with the project's economic analysis, we consider a 15 per cent increase in income (an endline average income of BDT 104,109.5 in the treatment group) as a good benchmark for our estimate of the minimum detectable effect. Our calculations assume 25 clusters in the treatment group (Phase 1 UPs) and 14 clusters in the control group (Phase 2 UPs), in line with the design exposed in section V.A.2. Finally, we assume 15 per cent attrition between the baseline and follow-up data collections,[26] statistical power of 80 per cent and a statistical significance parameter of 5 per cent.

The results in Table 6~~Table 6~~ show that if we can measure yearly income from 68 households in each cluster (on average) at endline, we will be able to detect an impact of +14.9 per cent in income with respect to the control group (in line with the income gains assumed in the project's economic analysis). Therefore, adjusting for 15 per cent attrition, the IE team and project team agreed on a target sample size of 3,120 observations at baseline, equally split across UPs.

Table 6. Sample size calculations based on income as the outcome variable

	Cluster size				
Baseline income (BDT)	**Endline**	**Baseline (attrition)**	**Baseline N**	**MDE**	**Endline income (BDT)**
90,530	68	80	**3,120**	**+14.9%**	**103,991**

Source: LORTA calculations using baseline data from project areas.
Notes: The cluster size refers to the number of households to be surveyed – on average – in each of the 39 clusters.
Abbreviations: BDT = Bangladesh taka, MDE = minimum detectable effect.

[24] The sample size calculations take into account the clustered nature of the IE design.
[25] The survey reported some households earning BDT 0 per month from their primary income source, while some others reported earning as much as BDT 200,000 per month, or about USD 2,350.
[26] We assume a gap of 12 months between the baseline and follow-up data collections.

2. Sampling frame and sampling for the baseline survey

UNDP carried out a full census of the households living in the project areas to collect the information needed to compute the vulnerability scores that determine the households' eligibility to receive the programme activities. Beneficiary lists were finalized in September 2021, after validation in the field by UNDP. The IE team used said lists to select the baseline survey sample.

Before selecting the beneficiaries to interview at baseline, the sampling frames were cleaned as follows:

- Duplicates in unique household identification numbers were dropped.
- Duplicates in national identification numbers were dropped.
- Seemingly erroneous national identification numbers were dropped.
- Households that could not match the census data were dropped.

Table 7~~Table 7~~ shows the number of units remaining in the beneficiary lists for each upazila after the cleaning procedure.

Table 7. Number of observations in the sampling frame

Upazila	Number of observations in the original sampling frame	Number of observations in the cleaned sampling frame
Assasuni	5,975	5,022
Dacope	4,656	4,400
Koyra	2,265	2,177
Paikgachha	2,361	2,063
Shyamnagar	1,709	1,582
Total	***16,966***	***15,244***

Source: LORTA, based on project beneficiary lists.

Using the cleaned sampling frames,[27] the baseline sample was selected for each upazila separately. In each UP (within a given upazila), the IE team randomly sampled 80 households to be interviewed at baseline (in line with the overall target of 3,120 observations), with an additional 90 households per UP as backups in case some of the 80 households on the main list could not be interviewed. The IE treatment group (Phase 1 UPs) counts 2,000 observations, and the IE control group (Phase 2 UPs) 1,120 observations, spread evenly across all UPs.

[27] All 39 UPs and 101 wards are still represented in the sampling frame after cleaning.

VI. IDENTIFICATION OF CAUSAL IMPACTS

A. MAIN EFFECTS

The suggested IE design establishes a suitable control group for robust measurement of the causal impacts of the LH component. The control group (Late LH) will consist of eligible households that have similar vulnerability profiles to those in the treatment group (Early LH). The random selection of groups ensures that there is no bias introduced by targeting some specific areas or households in priority due to some other factors that may or may not be observed or measurable.

The chosen clustered phase-in RCT design will allow the direct estimation of intention-to-treat (ITT) effects (i.e. the impact of being exposed to [or offered] treatment, or – in other words – the effect of being offered the LH project activities). If all units assigned to treatment do indeed take up treatment, and none of the control units does, the ITT will be equal to the average treatment effect on the treated, as defined in the usual potential outcomes framework.[28] If the adoption or participation rate in the treatment group is less than 100 per cent (but all control units remain untreated), a simple rescaling of the ITT by the adoption rate in the treatment group will provide the treatment effect on the treated (TOT). Finally, if there is imperfect compliance (i.e. project participation is less than 100 per cent in the treatment group and more than 0 per cent in the control group), the random treatment assignment variable can be used in an instrumental variable approach to recover the local average treatment effect (LATE) (i.e. the effect of the intervention on those who adopt the project [or not] in compliance with their assigned treatment status).

The ITT remains a valid estimate even under imperfect compliance or with limited participation in the treatment group. In such cases, the ITT represents a lower bound to the impact of actually receiving treatment. Therefore, the ITT remains an intuitive and policy-relevant quantity as long as participation is very high in the treatment group and very low in the control group. Provided the integrity of the design is preserved (see section VI.C), the impact estimates should exhibit strong internal validity (i.e. the measured impact can be effectively attributed to the impact of LH activities on target beneficiaries in the specific context of the project).

It is likely that several factors will dampen the external validity of the results. For instance, LH activities specifically target women. Therefore, the measured household-level impacts, while attributable to the project, intrinsically depend on the cultural context and, in particular, on gender roles and intra-household dynamics in these regions of Bangladesh. The results might not carry over to other contexts where attitudes towards gender and gender roles differ. Similarly, the types of adaptive LH promoted by the project are quite specific to the natural, environmental and traditional contexts of the target areas. The study results can only be relevant to other projects that promote similar LHs in similar contexts (topology, weather, salinity, etc.). Furthermore, project placement was not random, and target areas were selected by the project specifically because their populations are the most vulnerable in the region. These areas also experience extreme weather events every year, most commonly cyclones and storm surges. The high vulnerability profile of the project areas and their high exposure to frequent shocks make them hard to compare with other, less extreme contexts. The external validity of the study is also hard to assess because of the global COVID-19 pandemic. Bangladesh was particularly affected in 2021, and uncertainty remains high despite recent improvements at the time of writing.

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[28] Theoretically, this is true if randomization is successful in eliminating bias and if the stable unit treatment value assumption holds. This assumption states that a given unit's treatment status does not influence the (potential) outcome of another unit. For an intuitive treatment of the potential outcomes framework, see Angrist and Pischke (2008).

B. HETEROGENEOUS EFFECTS

The expected heterogeneous effects of the project relate to the ancillary EQs laid out in chapter IV, namely M1, A1 and A2.

1. DW SOLUTIONS

As explained in the ToC (chapter III), one key mechanism of the success of the project is to influence the way women allocate their time. The rationale is that the DW solutions provided by the project will reduce the time allocated by women to collect water and hence allow them to allocate more of their time to income-generating activities, in particular the adaptive LHs promoted by the project. A crucial aspect is therefore how much time women actually gain thanks to the DW component of the project. More specifically, one expects that women living in households benefiting from HHDW will free up more time than women in households benefiting from CBDW, hence potentially enjoying larger benefits from the LH component through their ability to invest more time in adaptive LHs.

As is apparent in the randomization procedure presented in section V.A.3, eligibility for different DW solutions was not accounted for in the evaluation design. Nonetheless, given that LH-eligible households were sampled randomly within each cluster for data collection (see section V.B), we expect that both types of DW solution will be represented in both the Phase 1 and Phase 2 areas.[29] This will allow estimation of whether beneficiaries from HHDWs enjoy larger gains than beneficiaries of CBDWs.[30]

The proposed analysis comes with two caveats. First, the assignment to different types of DW solution was not random. As such, the results cannot be interpreted as causal to the extent that being eligible for HHDW or CBDW might correlate with unobserved characteristics that potentially influence the outcome variable. Second, the study was not powered for heterogeneity analysis because the sample size required for direct comparison of treatment effects was unfeasible given the expected magnitude of the project impacts and the moderate number of clusters considered for the randomization procedure. At the time of writing, it is reasonable to expect that the difference in treatment effects of the LH component between HHDW and CBDW beneficiaries will not be statistically significant at conventional levels of confidence unless project impacts are larger than anticipated and the difference between group-specific impacts is also large.

2. TYPE OF LH ACTIVITY

As explained in chapter IV, there was no feasible randomization-based IE design to answer EQ A2 directly in a causal framework due to self-selection in the choice of adaptive LH by the WLGs (see the description of the LH project component in section II.A). Therefore, we propose to investigate EQ A2 through descriptive statistics based on endline and M&E data on income, sales and profits from adaptive LHs. We will compare average endline levels and growth from the baseline of the aforementioned outcomes across the various LH options, focusing on the most popular ones (depending on uptake of the various adaptive LHs promoted by the project). Interpretation of said comparisons will not be causal, as self-selection implies that confounding factors may influence both the choice of specific adaptive LHs and the outcome, and the proposed design does not allow such factors to be controlled for. In addition, there are as many as eight LHs promoted by the project, and the study's sample size does not provide enough power for meaningful comparisons between numerous treatment modalities. M&E data might allow the evaluation team to carry out part of the

[29] Drinking water activities are not subject to sequential implementation and will start in all project areas simultaneously.
[30] CBDW refers to both community-based and institution-based drinking water solutions, as both imply having to fetch water from outside the household.

proposed descriptive analysis for all Phase 1 beneficiaries of LH activities, provided they include data on the outcome variables of interest for all project beneficiaries.

C. Assumptions and limitations

The suggested IE design establishes a suitable control group for robust measurement of the causal impacts of the LH component. The control group (Late LH) will consist of eligible households that have similar vulnerability profiles to those in the treatment group (Early LH). The random selection of groups ensures that no bias is introduced by targeting some specific areas or households in priority due to other factors that may or may not be observed or measurable.

Randomization offers a simple and elegant framework to measure intuitive causal impacts. Nonetheless, the integrity of the design relies on one crucial aspect: implementing partners must follow the random assignment (i.e. implement only in the UPs that are assigned to Phase 1 during Phase 1, and not implement in other areas [Phase 2] until the endline data collection is completed). Real-time access to the project's M&E data and close collaboration with UNDP will allow the IE team to be reactive if there are signs of contamination of the control group.

If the integrity of the design is preserved, the envisioned design will allow the estimation of the causal effects of the LH intervention. Nevertheless, two key limitations of the IE design must be acknowledged, in terms of scope and time-horizon. First, as the experimental variation is relevant only for the LH intervention, the IE design does not allow estimation of the specific impacts of the DW and EWS project components on the outcomes of interest, nor of the overall impact of the project. Second, the short timespan between Phases 1 and 2 means that the study will focus on short-term effects (i.e. the medium- and long-term effects of the LH component will not be measurable unless the roll-out of activities in Phase 2 is further delayed or even cancelled).[31]

Furthermore, although the IE is focused on the LH component of the project, other project activities (i.e. the DW and EWS components) will be carried out at the same time. Exposure to DW and EWS activities might bias the impact estimates if DW and EWS are not implemented in all areas simultaneously or at the same pace and if the geographical patterns of DW and/or EWS implementation strongly correlate with random assignment to the LH phase-in. For instance, if by the time follow-up data are collected, EWS activities have not started everywhere and the areas where they have started are mainly part of the Phase 1 UPs, the proposed design would provide biased estimates of the impact of LH.[32]

The evaluation team will know from the start which households are eligible for the DW component, thanks to the lists prepared by UNDP. Therefore, the analysis can control for household eligibility for the DW component, and in particular eligibility for which DW solution. The EWS component essentially covers all households in the project areas, irrespective of their eligibility for DW or LH, which means that exposure to EWS activities should in principle be the same in Phase 1 and Phase 2 UPs. Information on exposure to EWS activities and the progress of DW activities should be available in the project's M&E data and will allow the IE team to know in which areas activities had been implemented when they started, and to control for it in the analysis if required. In addition, should the

[31] Only the effects that can realistically materialize before the roll-out of the second phase can be measured. In particular, given that LH interventions target income-generating activities that have production cycles of at least a few months, it is unclear whether beneficiaries in the "Early LH" group will have realized measurable gains thanks to the programme before the Late LH group starts receiving the intervention.

[32] The impact estimate would be a mix of the impact of LH and that of EWS. Given that the geographical placement of EWS activities would not be random, the EWS-related impact would be biased, hence so would the impact estimate based on the proposed IE design.

M&E data prove unavailable or incomplete, information on exposure to EWS and DW activities will be collected during Follow-up 1. One solution could be to introduce an extra source of experimental variation in the EWS component. If implemented according to a plan, this strategy could mitigate the aforementioned risk of misidentifying the main impact of interest (i.e. that of the LH component) and generate further learning opportunities.

Another risk relates to the current global health crisis due to COVID-19. At the time of writing, UNDP has successfully completed the census and baseline data collections. However, levels of uncertainty remain high regarding the timeline of project activities, as UNDP has already had to manage several delays due to the health situation in the country, facing several nationwide lockdowns. The project and evaluation teams will keep in close contact to react quickly should there be any new developments with regards to the health situation in the country and should UNDP be forced to amend its implementation plan in consequence. Such unforeseeable delays and changes in the implementation of the project in reaction to the COVID-19 pandemic could affect the IE, in particular the timing of the next data collection. It is therefore still unclear whether the IE will be carried out as planned.

VII. EMPIRICAL ESTIMATION

This chapter describes the various data sources used for the IE (VII.A), VII.B and VII.C discuss in detail the empirical strategy for the core analysis. VII.D discusses the strategy to deal with the challenge to measure one of the main outcomes of LH: income stability, while VII.E presents a number of robustness checks.

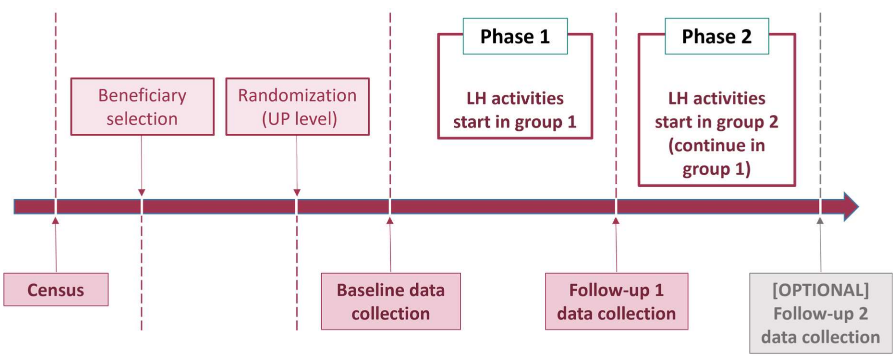
A. DATA

1. DATA SOURCES

In early 2021, UNDP carried out a full census of the households living in project areas in order to collect the information required to compute the vulnerability scores that determine households' eligibility for the project.[33] The census questionnaire was designed to collect a rich set of information on household sociodemographic characteristics, basic asset and income data, and household vulnerability. This information, in particular on household size, composition and demographics, will be linked to the baseline and endline data for the purpose of the IE. Selected variables from the census data were used to carry out preliminary balance tests after the randomization procedure (reported in Table 10~~Table 10~~ in the appendix). The census data cover 66,171 uniquely identified households.

The proposed IE strategy requires collecting data on key outcomes from Phase 1 and Phase 2 households just before the start of Phase 2 (endline survey). These data will be complemented by baseline data, which were collected in both groups before the start of programme activities (i.e. before Phase 1).[34] Phase 2 is planned to start after 12 months of input support for Phase 1 beneficiaries. The sequence of IE-related activities and how they relate to project activities is laid out in **Error! Reference source not found.**~~Figure 5~~.

Figure 5. Sequence of IE and project activities



Abbreviations: LH = livelihood, UP = union parishad.

[33] An initial baseline survey was carried out in 2019 by Practical Action Consulting. Information was collected on 3,000 households in all project areas, with an extensive scope ranging from sociodemographic characteristics, to income and vulnerability, to shocks and extreme weather events. Unfortunately, several shortcomings were identified in the data set during the scoping mission, and the data were deemed inappropriate for use in the IE. The evaluation team and UNDP jointly decided that a new baseline should be conducted.

[34] While in theory baseline data are not necessary when treatment is assigned at random, in practice baseline data will prove extremely useful to check the quality of the randomization procedure and to increase the precision of estimates in the final analysis.

The IE baseline survey was launched in September 2021 and was completed in October 2021. The survey focuses on collecting information on IE indicator variables from all study households, the other relevant pre-treatment data (e.g. household sociodemographics) being already covered in the census data.[35] Baseline data on key outcomes will be used for four purposes: (1) to carry out balance tests between the IE treatment and control groups; (2) in an exploratory variance analysis to gauge whether the correlation structure of the data warrants clustering the analysis at a level other than UPs (see section VII.D); (3) in combination with census data to determine whether some baseline household characteristics (unaffected by treatment) are strongly predictive of the outcome, warranting their inclusion in the analysis; and (4) to increase the precision of ITT estimates in the envisioned regression framework (see section VII.C).

The endline survey will focus solely on outcomes and will be the key to estimating the impact of the LH component of the project. The target sample at the endline will be the same as that identified for the baseline survey, irrespective of whether sampled households responded at baseline, with the intention to maximize sample size and statistical power. Thanks to the experimental design, the endline survey will also offer the opportunity to expand the baseline questionnaire if needed and collect data on extra indicators.[36]

Finally, the project's monitoring and information system will provide an overarching platform to gather and access M&E data. Table 8~~Table 8~~ summarizes the indicators that UNDP plans to monitor, the data sources for each indicator, and the frequency of monitoring. Table 8~~Table 8~~ only reports those indicators that are relevant for the proposed IE.

Table 8. Project M&E data relevant for the IE

Project component	Indicator	Unit of measurement	Means of verification (data sources)	Frequency
LH	Number of males and females benefiting from the adoption of diversified, climate-resilient LH options (fisheries, agriculture, etc.);	Number of people (females)	Database, trackers, web portal, M&E report	Annually
LH	Number of women in targeted wards with improved assets and income from climate-resilient LHs	Number of women	Training attendance sheet, input distribution muster roll, market engagement report and checklist	Quarterly
LH	Number of people benefiting from jobs and improved LHs in crisis or post-crisis settings, disaggregated by sex and other characteristics	Number of people	LH analysis report, job placement report	Annually
LH & DW	Proportion of time spent on unpaid domestic and care work, by sex, age and location	Proportion of time spent	Evaluation report, gender analysis report, government reports	Biannually/ middle and end of the project
DW	Number of males and females with year-round access to reliable and safe DW	Number of males and females	DPHE registration database, water option database, water quality monitoring report, O&M survey results	Half-yearly
DW	Total number of project-established climate-resilient DW systems operational	Number of climate-resilient DW systems	Project M&E database, water options installation report, O&M survey results	Quarterly

[35] A few dimensions from the census survey are also present in the baseline survey for areas in which the census data needed more detail or new (and improved) measures.
[36] It is also possible to collect another round of follow-up data after Phase 2 is completed (i.e. "Follow-up 2") to investigate the impact of longer exposure to treatment on key outcomes.

PROJECT COMPONENT	INDICATOR	UNIT OF MEASUREMENT	MEANS OF VERIFICATION (DATA SOURCES)	FREQUENCY
EWS	Existence of operational end-to-end multisectoral EWS to limit the gender-differentiated impact of: a) Natural hazards b) Economic crises c) Other risk factors (slow onset changes: salinities)	Multisectoral EWS	Study/research report	Middle and end of the project
EWS	Number of males and females with access to timely, gender-responsive early warning information	Number of males and females	Training attendance sheet, event report, muster roll	Quarterly
EWS	Proportion of women in leadership positions within prevention and recovery mechanisms	Proportion of women	Evaluation report, gender analysis report, government reports	Biannually/ middle and end of the project
All	Number of people supported with LHs, water options and EWS information	Number of people	Training attendance sheet, event report, muster roll, assessment report	Annually
All	Total number of direct and indirect beneficiaries	Number of people (males & females)	Muster roll, training record, activity tracker, database, web portal	Annually

Source: LORTA, based on project documents.
Abbreviations: DPHE = Department of Public Health Engineering, DW = drinking water, EWS = early warning system, IE = impact evaluation, LH = livelihood, M&E = monitoring and evaluation, O&M = operation and maintenance.

2. ATTRITION

As the IE plan sets out to interview the same households at baseline and endline, attrition mechanically becomes a concern for two reasons: (1) it can jeopardize the study's statistical power, and (2) it can threaten the study's internal validity.

With respect to the first issue, the sample size calculations presented in section V.B.1 assume up to 15 per cent attrition in the sample, which gives some buffer in terms of statistical power. In addition, thanks to the experimental nature of the design, one could consider expanding the endline sample beyond the target households originally identified if attrition at follow-up seems too high. Indeed, we stress again that, while extremely valuable, baseline data are not an absolute requisite for the analysis of a well-implemented RCT. Hence, increasing the sample size at the endline with observations from beneficiaries that did not answer the baseline survey is a common strategy to preserve statistical power in RCTs.

Regarding the second issue, attrition may threaten the internal validity of the proposed IE when it is selective (i.e. when the attrition rate is significantly different in the Phase 1 and Phase 2 groups). However, this concern is mitigated by at least two factors. First, the relatively short time lapse (about 12 months) between the baseline and follow-up data collections limits the risk of attrition in the sample as a whole. Second, the study control group (i.e. Phase 2 UPs) consists of project beneficiaries, which means that they will be frequently tracked by the project for M&E purposes, thereby increasing the chances of being able to track them at the endline if necessary.[37] In addition, Phase 2 beneficiaries will already benefit from some project activities during Phase 1, in particular from the DW component,

[37] Only LH activities will be delayed in Phase 2 UPs. Project activities relating to drinking water and EWS will be implemented, effectively making these UPs "active" project areas and hence fully part of the M&E system.

which could therefore decrease the likelihood of migration in that group – assuming that benefiting (or not) from a project is an important driver of the decision to migrate.[38]

3. Processing of IE survey data

After data collections (baseline and endline) are completed, the LORTA team will carry out ex post data quality checks. In particular, the team will examine the consistency of key outcome variables (or variables used to create such outcomes) to detect, for example, outliers, missing data and duplicates. The LORTA team will then share its findings with UNDP to clarify where the identified inconsistencies might stem from and potentially ask for corrections. In addition, the LORTA team will seek the assistance of UNDP to ask the data-collection firm in charge to recode the string entries of "Other, specify" fields into existing answer categories whenever possible. After the quality checks are completed, the remaining duplicates will be dropped from the data set, either completely or by randomly keeping one of the duplicate observations.

The next step will be the construction of outcome variables. In particular:

- Household expenditure and income will be converted to yearly amounts.
- A household asset index (wealth proxy) will be constructed following a principal component analysis.
- Household food insecurity will be measured by the FCS following the World Food Programme methodology (WFP, 2008) and by the HFIAS of the US Agency for International Development's Food and Nutrition Technical Assistance Project (Coates, Swindale and Bilinsky, 2007).

Once all the variables necessary for the analysis are generated, we propose to trim the data following the methodology used in Crépon and others (2015):

- For all main continuous outcome variables at the endline, compute the ratio of the variable value to the 90th sample percentile.
- Take the maximum ratio for each observation across said outcomes, and rank observations based on this maximum value.
- Drop the 0.5 per cent of observations with the highest ratios.

The rationale for trimming outliers is that the regression framework proposed for the analysis (see sections VII.B and VII.C) relies on ordinary least squares (OLS), an estimator that is famously sensitive to extreme observations due to its focus on the conditional mean. However, outliers do not always consist of measurement errors or data mistakes and are precious in providing information on units that actually do experience extreme realizations of the outcome variable. The approach suggested in Crépon and others (2015) aims to strike a balance between the two (i.e. to stabilize OLS estimates while retaining meaningful information).[39]

B. Average treatment effects

The phase-in clustered RCT provides a straightforward analytical framework to estimate the short-term impacts of the LH component of the project. The impacts of interest can be recovered through linear regression of the form:

$$Y_i = \alpha + \beta T_i + S_{upz} + e_i \qquad (1)$$

[38] The evaluation team considers that migration is the most likely source of attrition in the given context and timeline.
[39] On this topic, see the discussion in Crépon and others (2019).

where Y_i is the value of the outcome of interest at endline for household i, α is a constant, T_i is a dummy variable equal to 1 if household i lives in a Phase 1 UP (and 0 otherwise), S_{upz} is a set of dummy variables controlling for stratification at the randomization stage (i.e. upazila-level fixed effects), and e_i is the household-level error term clustered at the UP level.[40] In that setting, β measures the ITT effect, which captures the impact of being exposed to the project.

As mentioned in section VI.A, in case of perfect compliance, the ITT is equivalent to the average TOT (i.e. the impact of actually taking up treatment). In case of imperfect compliance (either one or two sided), the ITT can be rescaled as follows:

$$\tilde{\beta} = \frac{\beta}{E(D_i|T_i = 1) - E(D_i|T_i = 0)} \qquad (2)$$

Where T_i is individual i's random treatment assignment as defined in equations (1) and (2), D_i is equal to 1 if individual i actually received treatment and 0 otherwise, and $E(.)$ is the expectation operator. We can see easily that under perfect compliance, equation (2) gives the ITT as defined previously ($E(D_i| T_i=1)=1$ and $E(D_i| T_i=0)=0$). In the case of one-sided non-compliance in the treatment group, (i.e. ($E(D_i| T_i=1)<1$ and $E(D_i| T_i=0)=0$), equation (2) yields the TOT. Finally, if there also exists imperfect compliance in the control group (i.e. $E(D_i| T_i=0)>0$), equation (2) will yield the LATE.

In practice, in the linear regression framework proposed here, the TOT or LATE will be recovered via two-stage least square estimation, using random treatment assignment (T) as an instrument for treatment status (D). The estimation of the TOT (or LATE) via two-stage least square estimation will directly provide correct statistical inference.

C. ADJUSTED AVERAGE EFFECTS

Athey and Imbens (2017) recommend favouring the analysis of experimental data through a simple comparison of the treatment and control groups that accounts for design specificities (i.e. regression equation (1)). Indeed, this direct, simple comparison allows the estimation of unbiased treatment effects thanks to randomization. In addition, choosing this straightforward (and correct) specification can prevent specification searches by the researchers.

Nonetheless, the precision of ITT estimates may be improved by adjusting the estimation procedure with the inclusion of baseline values of selected covariates. In particular, McConnell and Vera-Hernández (2015) show that the inclusion of baseline outcome values as a covariate increases the precision of impact estimates, and such specification typically dominates a simple post-intervention comparison (as in equation (1)) in terms of statistical power. Therefore, thanks to the availability of baseline data, we can augment regression equation (1) by including the pre-treatment (i.e. baseline) value of the outcome variable as an extra covariate:

$$Y_i = \alpha + \beta T_i + \gamma Y_{i0} + S_{upz} + e_i \qquad (3)$$

where Y_{i0} is the baseline value of outcome Y for household i. All other parameters are the same as in equation (1). Both regression equations (1) and (3) will be used in the main analysis, as is good practice in most RCTs: the unadjusted estimates from regression equation (1) will serve as "benchmark" results, while regression equation (3) is used to get more precise estimates through the inclusion of a covariate that does not involve specification search, namely baseline outcome values.

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[40] In that instance, clustering is used to account for the experimental design and the fact that treatment is assigned at the UP level. As MacKinnon, Nielsen and Webb (2022) put it: "When the regressor of interest is a treatment dummy, and the level at which treatment is assigned is known, then it generally makes sense to cluster at that level […] If treatment is assigned by cluster, […] it never makes sense to cluster at a level finer than the one at which treatment is assigned."

Furthermore, we will consider another adjustment to the main estimates in order to measure the heterogeneous treatment effects by type of DW solution, as discussed in section VI.B. The latter can be estimated by augmenting the main regression specification in equation (3) as follows:

$$Y_i = \alpha + \beta T_i + \delta HHDW_i \times T_i + \mu HHDW_i + \gamma Y_{i0} + S_{upz} + e_i \quad (4)$$

where $HHDW_i$ is equal to 1 if household i is eligible for an HHDW (and 0 otherwise). Parameter β captures the ITT for households eligible for DW solutions other than HHDW, while δ will measure the additional impact of LH activities for HHDW-eligible households.

D. INCOME STABILITY

A clear expected outcome of the LH component is to provide beneficiaries with the means to generate income frequently throughout the whole year, and hence to stabilize income. The concept of stability clearly relates to the way a status or process changes (or not) over time. In the context of the present IE, measuring stability is a challenge given that impacts are expected to be measured not later than 1 year after the implementation. While the plan is to gather panel data by interviewing the same sample of beneficiaries at baseline and endline, there is no readily available measure of household income stability with only two data points – one before and one after the intervention.

To understand the issue, assume we use the change in income between baseline and endline as a measure of income stability, with the idea that income is stable if it does not change (or changes little) over time. Furthermore, assume that the intervention generates positive income gains in the treatment group (Phase 1 UPs) while income remains the same in the control group (Phase 2 UPs). In that case, our measure would indicate that income is in fact more stable in the control group. The reason is that the impacts on income levels and income stability have different time-horizons. In the first period, income increases thanks to the programme. Only after at least one extra period can it be assessed whether the new, higher level of income is stable over time. Due to constraints with regard to the implementation timeline, there is no possibility to measure income a second time (and after a reasonable time lapse) before rolling out the LH intervention in Phase 2 UPs.

In such situations, it is common to rely on a proxy to study an unmeasurable outcome or to investigate another outcome variable that captures one dimension of the phenomenon at hand. In that spirit, we propose two approaches to investigate treatment effects on income stability: (1) use a regression model to estimate the effect of the intervention on expected (future) income volatility, and (2) estimate the impact of the LH component on income diversification.

1. INCOME STABILITY AS EXPECTED VOLATILITY

a) Conceptual framework

We propose a regression model-based approach to estimate the impact of the intervention on income volatility. Our approach is based on that of Chaudhuri, Jalan and Suryahadi (2002) (CJS henceforth), which developed a framework to measure vulnerability as expected poverty. Understanding vulnerability as expected poverty as the probability of falling into poverty in the future, the authors propose an empirical method to estimate the expected (future) level and the volatility of household expenditure, which in turn are used to calculate said probability.

The CJS method is tailored to cross-sectional data, which is adapted to our setting. While the end goal of the CJS method is to calculate vulnerability as expected poverty, an intermediary step involves the estimation of expected volatility. An interesting by-product of this intermediary step is that one can estimate the effect of specific variables on expected volatility. Although the authors originally focused on household expenditure, their method is flexible and can be used for household income under similar assumptions.[41] As a consequence, we propose to use the estimated expected volatility of income as a measure of income stability. We will therefore follow the CJS approach up to the step where we can estimate the impact of the intervention on expected income volatility.

b) Methodology

As explained in CJS and in Hoddinott and Quisumbing (2010), the starting point of the method is to define a functional form for the stochastic generating process of household income, which we propose to be as follows:

$$\ln(Y_i) = X_i\beta + e_i \qquad (5)$$

where the dependent variable is the logarithm of household income, X_i is a set of household characteristics, and e_i is a disturbance term with mean zero capturing household-level income shocks that generate differences in observed income between households that are observationally similar. A key contribution of CJS is to relax the assumption that disturbances e_i are homoscedastic and instead specify a functional form for the variance of idiosyncratic shocks:

$$\sigma^2(e_i) = X_i\theta \qquad (6)$$

Where θ is a parameter to be estimated. In other words, CJS explicitly allows for heteroscedastic errors. The regression framework defined above allows the estimation of the expected level and variance of log income as, respectively:

$$\hat{E}[\ln(Y_i)\,|X_i] = X_i\hat{\beta}$$
$$\hat{V}[\ln(Y_i)\,|X_i] = X_i\hat{\theta}$$

Where E[.] and V[.] are the expectation and variance operators, respectively, and the hats indicate quantities that are estimated. CJS suggest using the method designed by Amemiya (1977) to estimate β and θ via three-step feasible generalized least squares (FGLS) with the following procedure:

1. Equation (5) is estimated via OLS to predict residuals $\hat{e}_i$. Their square is used as a raw estimate of the variance of the disturbance term and used as the dependent variable in the following regression:

   $$\hat{e}^2_{i,OLS} = X_i\theta + \nu_i \qquad (7)$$

   where ν_i is an error term.
2. The predictions from estimating equation (7) via OLS are used to transform the equation as such:

   $$\frac{\hat{e}^2_{i,OLS}}{X_i\hat{\theta}_{OLS}} = \left(\frac{X_i}{X_i\hat{\theta}_{OLS}}\right)\theta + \frac{\nu_i}{X_i\hat{\theta}_{OLS}} \qquad (8)$$

   where $\hat{\theta}_{i,OLS}$ is the estimate of θ obtained via OLS in step 1.
3. Estimating equation (8) via OLS yields an asymptotically efficient FGLS estimate of θ (denoted $\hat{\theta}_{FGLS}$) and a consistent estimator of the variance of idiosyncratic shocks (i.e. the volatility of log income), given by:

   $$\hat{\sigma}^2(e_i) = X_i\hat{\theta}_{FGLS} \qquad (9)$$

[41] See Bronfman and Floro (2014).

Essentially, our strategy consists of including the treatment variable in the set of covariates used to model log income. The corresponding FGLS coefficient in equation (9) therefore provides an estimate of the impact of the intervention on income volatility.

In principle, correct inference on $\hat{\theta}_{FGLS}$ can be made by dividing the coefficient standard error by the regression standard error. However, due to a complex experimental design, the analysis must also account for cluster-level treatment assignment. A block bootstrapping approach seems appropriate to account for potential cluster-level correlation in household income (Cameron, Gelbach and Miller, 2008), with the following steps:

1. Estimate the coefficient of interest in the original sample.
2. From the original sample with G clusters, re-sample G clusters with replacement (G = 39 in the present study sample). This is the bootstrap sample.
3. For each bootstrap sample, estimate the FGLS coefficient of interest (as in Step 1).
4. Repeat Steps 2 and 3 a large number of times. We suggest 999 repetitions.
5. Use the observed distribution of the bootstrap estimates to infer the coefficient estimated in Step 1.

c) Empirical specification

A key aspect of the approach is to specify a model in equation (5) that is predictive of log income. In practice, the choice of observable covariates to include in the predictive model is based on theory, findings from empirical studies, researcher experience and, of course, data availability. Table 9~~Table 9~~ draws the list of household-level characteristics we propose to include in regression equation (5).

Table 9. Household characteristics to predict log income

VARIABLE	REFERENCES
Age of HH head	GH09; IWK10; BF14; FAO15
Age of HH head squared	IWK10; BF14
Gender of HH head (DV)	IWK10; BF14; FAO15
Education of HH head	GH09; BF14; FAO15
Female-headed HH	GH09
HH size	GH09; FAO15
Presence of children (DV)	BF14
Economic dependency ratio	BF14; FAO15
Share of female HH members	IWK10; FAO15
Land ownership (DV)	GH09
Wealth (HH asset index)[a]	BF14; FAO15
Size of farmland	IWK10; [FAO15][b]

Source: LORTA.

Notes: To save space, we use abbreviations to refer to empirical applications of the CJS method: GH09 = Günther and Harttgen (2009), IWK10 = Imai, Wand and Kang (2010), BF14 = Bronfman and Floro (2014), FAO15 = FAO (2015).

Abbreviations: CJS = Chaudhuri, Jalan and Suryahadi (2002), DV = dummy variable, HH = household.

[a] Household wealth is proxied by an asset-based wealth index estimated via principal component analysis.

[b] FAO (2015) uses land size, without specifying whether it is total land or farmland.

In the OLS-based predictive model of equation (5), log income is measured at the endline, while covariates include the baseline values of the variables listed in Table 9~~Table 9~~. The model will also include the baseline value of log income as an additional explanatory variable.

The set of covariates used in the CJS method allows the inclusion of community or regional-level variables.[42] This possibility allows the stratification of the study sample (due to the randomization design) to be controlled for through the inclusion of upazila-level dummy variables, similar to regression equation (1). In addition, right-hand-side variables will include a dummy variable indicating assignment to Phase 1; the corresponding FGLS coefficient will provide an estimate of the impact of the intervention on income volatility, the proposed proxy for income stability.

d) Assumptions and limitations

The CJS approach relies on a number of assumptions that must be kept in mind when interpreting the results. Indeed, the OLS-based regression framework specified in equations (5) and (6) assumes that household income follows a log-normal distribution (which is typically a fair assumption in practice) and that heteroscedastic idiosyncratic shocks can be modelled as a linear function of household observables. As this cross-sectional model is used to predict future income (and its volatility), the model implicitly assumes that said shocks are independent and identically distributed over time for each household.[43] Essentially, the assumption is that cross-sectional income variance is a good estimate of inter-temporal variance (Günther and Harttgen, 2009). Therefore, the method requires a large enough sample so that the realizations of income observed at a given time represent positive shocks as well as negative ones (i.e. the sample must include some households that experience “good times” and others “bad times”) (Imai, Wand and Kang, 2010). Similarly, this approach “is unlikely to reflect large unexpected shocks, if we use the cross-section data for a normal year” (Imai, Wand and Kang, 2010).

In summary, the CJS approach requires that economic conditions – and the environment at large – are relatively stable over time, at least to the horizon relevant for the predictions of the model.[44] It rules out uncertainty about future income as stemming from uncertainty about the future state of the economy.

2. Income diversification and income stability

Achieving better income stability can be understood as a consequence of a household’s ability to minimize risks and cope with shocks. The literature on rural LHs in developing countries has long proposed that income diversification is an efficient strategy for rural households to minimize risks (Barrett and others, 2001) as well as sustain their standard of living (Ellis, 2000). For that reason, household income diversification is closely related to income stability, in particular in areas prone to frequent extreme weather events, such as those studied in the present IE. For instance, Bandyopadhyay and Skoufias (2013) observe higher income diversification in areas of Bangladesh that are more prone to floods, confirming the role of income diversification as an ex ante risk mitigation strategy. In another study on Bangladeshi households, Rehan and others (2019) establish that survival is the main motivation for poorer households to diversify their income.[45]

Conceptually, income diversification can therefore be seen as a potential determinant of income stability through its role as a risk mitigation device, leading to a higher degree of income smoothing thanks to a better ability to cope with risks. Due to the impossibility of measuring income stability

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[42] For instance, in applications of the CJS method, Imai, Wand and Kang (2010) and Bronfman and Floro (2014) include regional dummy variables, while Günther and Harttgen (2009) include community-level variables.

[43] Intuitively, this can be seen as similar in spirit to correlated random effects in panel data models where time invariant unobservable household effects are modelled as a linear function of household observed characteristics, as famously introduced by Mundlak (1978) and Chamberlain (1982).

[44] As data on annual household income will be used for the present analysis, we assume the horizon of the predictions to be one year.

[45] As opposed to richer households, which typically diversify to maximize returns and accumulate wealth.

directly with the available data, investigating the impact of the interventions under scrutiny on income diversification is an insightful complement to studying expected income volatility. Importantly, the possibility of diversifying income can be hindered by a lack of capital (Goulden and others, 2013) and depends on the availability of appropriate LH options (Rahman and others, 2008). The LH component of the project under scrutiny addresses precisely these two barriers, which is a good reason to expect the intervention to cause higher income diversification, which can be interpreted as an improved capacity to minimize risks and cope with shocks, an important step towards a more stable income.

A common approach to measuring household income diversification is to use a concentration (or diversification) index similar to the Herfindahl index famously used in industrial economics. Various income diversification indices have been used in the literature to study the phenomenon in developing countries.[46] Palan (2010) reviews the strengths and weaknesses of several popular diversification indices and concludes that the Hirschman–Herfindahl Index (HHI) and the Shannon Entropy Index are the most comprehensive measures of specialization (or diversification). However, the HHI has a clear advantage over the Shannon Entropy Index because it allows for income shares equal to zero (as easily seen in equation (10) below), whereas the Shannon Entropy Index does not (see Palan, 2010). The present study will use the inverse HHI[47] (following Idowu and others, 2011) as a measure of household *i*'s overall income diversification, calculated as follows:

$$D_i = \left(\sum_{j=1}^{n} S_{i,j}^2 \right)^{-1} \tag{10}$$

where $S_{i,j}$ is the share of household *i*'s income from source *j*, such that $\sum_{j=1}^{n} S_{i,j} = 1$. Income diversification measure D_i will be constructed based on income shares from the following sources:[48]

- Crop production
- Livestock
- Agricultural wage employment
- Wage employment in non-agricultural activities
- Non-farm household enterprises (self-employment)
- Transfers
- Other sources

Essentially, by squaring the shares, the HHI gives more weight to large shares, and a higher value of HHI hence represents a higher degree of concentration (i.e. less diversification).[49] By inverting HHI, a higher value of D_i represents a higher degree of overall income diversification. The endline analysis will use D_i as an outcome variable when estimating average treatment effects through regressions, following the specifications shown in equations (1) and (3). Therefore, a positive ITT will show a positive impact of the LH component on income diversification.

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[46] For example, FAO (2015) use the Margalef index for their study on livelihood diversification in Malawi, while Idowu and others (2011) prefer the (inverse) Herfindahl index to investigate non-farm income diversification in south-west Nigeria. Torres and others (2018) study agricultural diversification in the Ecuadorian Amazon with the Shannon equitability index.

[47] In studies of income diversification in Bangladesh, Sherf-Ul-Alam and others (2017) and Rehan and others (2019) use the Simpson index of diversification, which is the reciprocal of HHI and hence qualitatively similar.

[48] In line with the income sources defined by the Rural Income Generating Activities project conducted by the World Bank and the Food and Agriculture Organization of the United Nations. See Carletto and others (2007).

[49] The HHI takes equi-proportion as a reference and hence as its lower bound. In other words, the higher the HHI, the further away from the reference point of equi-proportion (i.e. the more uneven the importance of the various income sources in total household income).

E. ROBUSTNESS CHECKS

The empirical strategy described in sections VII.B and VII.C should provide unbiased estimates of average treatment effects (ITT and TOT) and correct statistical inference once the experimental design and potentially confounding covariates are accounted for.[50] In the next paragraphs, we suggest additional analyses to check the robustness of the main results.

1. COVARIATE ADJUSTMENT

The inclusion of additional covariates typically follows a few key guidelines:

- Covariates should be prognostic (i.e. strongly predictive) of the outcome variable.
- Covariates should be unaffected by treatment.
- The number of covariates should be much smaller than the sample size.

However, Athey and Imbens (2017) advocate for analysing randomized experiments through simple comparisons of the treatment and control groups without adjusting for covariates. The authors warn that precision gains from covariate adjustment are usually moderate in practice and that the inclusion of covariates may even (slightly) hurt precision in finite samples if they are not predictive of the outcome. Therefore, we consider that there are potential precision gains to the inclusion of baseline outcome values as additional covariates, as in regression equation (3) – drawing on the result from McConnell and Vera-Hernández (2015) (see section VII.C) – but believe that, from a conceptual standpoint, the proposed experimental design does not warrant adjusting the analysis for other covariates.

Athey and Imbens (2017) note a few instances where covariates may help correct potentially biased estimates, for instance when randomization has been compromised, even if the initial assignment was done correctly. In the proposed IE, balance tests on baseline data will be carried out. Nevertheless, we will not systematically adjust the analysis for covariates that show statistically significant imbalances at baseline. Indeed, some statistically significant differences in average characteristics between the treatment and control groups are expected to happen by chance, especially when balance tests are carried out on a large number of covariates. These imbalances do not mechanically invalidate the experimental design, nor do they systematically warrant adjusting the analysis. Imbalances only matter for covariates that are prognostic of the outcome variable.[51]

To select relevant covariates, we will identify potential confounders using balance tests and explore whether they are also strong predictors of the key outcome variables. If the proposed exploratory analysis yields a large number of covariates to consider for regression adjustment, we propose to follow the two-step robust procedure of Belloni, Chernozhukov and Hansen (2014), as suggested in Crépon and others (2019), to avoid specification search and to specify the set of covariates transparently and systematically.

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[50] The inclusion of baseline value covariates will control for potential biases in impact estimates due to group imbalances in characteristics that are strongly predictive of the outcome; see section VII.C for details on the selection of said covariates.

[51] In practice, balance tests are specified so as to account for the structure of the design and of the analysis (i.e. accounting for stratification and clustering). We will complement tests on individual covariates by an "omnibus" test of joint significance for all covariates under consideration. This omnibus test is carried out by running a regression of the treatment variable on the full set of covariates considered for the balance tests; the test corresponds to the joint F-test of this regression.

2. BIAS AND CONSISTENCY

As explained in section VII.A, the target sample at the endline will be the same as that identified originally at baseline. Therefore, we expect that sample composition will differ between the two data sets, either due to baseline observations lost to follow-up or to respondents being interviewed at the endline but not found at baseline. As a consequence, there will be two potential study samples:

- Sample 1: only units with both baseline and endline data
- Sample 2: all units observed at the endline

Sample 1 can be used in regressions following either specification (1) or (3), while Sample 2 can only be used in regressions following specification (1) (i.e. without baseline covariates). For the reasons explained above, we anticipate that Samples 1 and 2 will not consist of exactly the same households, and we expect that Sample 2 will count more observations. Therefore, we will use Sample 1 in the main analysis for regressions that follow specifications (1) and (3) to ensure comparability between estimates (i.e. restrict the endline sample when estimating (1)).

As a robustness check, we propose to report the results using Sample 2. While estimator bias is a property that does not depend on sample size, we may obtain different estimates for the ITT when using Sample 2 if there is selective attrition at baseline with respect to endline (i.e. selection bias in the pool of baseline respondents in terms of the experimental group or of potential outcomes). This check will inform us of the stability of the study sample and the ITT estimate. In addition, estimates based on Sample 2 will provide a check of the consistency of the chosen ITT estimator.

3. STATISTICAL INFERENCE

In the main analysis based on regression equations (1) and (3), standard errors will be clustered at the UP level because treatment was randomly assigned at that level. Although clustering at the UP level is conceptually sound and in line with "design-based" inference (Abadie and others, 2020), there is a risk that "conventional" analytical clustered standard errors are biased downward due to the moderate number of clusters (39) in our study (see Cameron, Gelbach and Miller, 2008). We suggest using randomization inference as a robust method to provide correct inference in a complex design, even with few clusters. Randomization inference is based on permutations that allow testing of sharp null hypotheses. For the proposed IE, the sharp null of interest will be that of "no treatment effect for any unit in the sample". This differs from the typical null hypothesis of "no average treatment effect", for which the regression-based approach discussed in section VII.B gives a direct test. (The weaker hypothesis of "no average treatment effect" is implied by the sharp null.) The algorithm to conduct randomization inference is straightforward:

1. In the original sample, generate a "fake" treatment variable using the same (random) assignment rule as for the actual randomization procedure.
2. Estimate and store the desired quantity based on the "fake" treatment variable, in our case the ITT, following the regression specification in equation (3).[52]
3. Repeat Steps 1 and 2 a large number of times (e.g. 5,000).
4. The sharp p-value is given by how often (in percentage) the quantity estimated in Step 2 is larger than the quantity estimated with the actual treatment.

The advantage of randomization inference is that it does not depend on modelling, but rather considers randomization itself as the source of uncertainty in the estimated statistics. As such, it mechanically

[52] This approach is valid under the sharp null of no treatment effect. In cases where the sharp null assumes a non-zero treatment effect, the procedure to account for covariates in randomization inference is different.

takes into account non-trivial design elements, such as stratification and clustering. This approach is only valid for ITT effects and not for other quantities, such as the TOT or LATE. For more details on randomization and inference, see Heß (2017) and Young (2019).

4. MULTIPLE HYPOTHESIS TESTING

When a large number of comparisons are investigated in one experiment, the probability of falsely rejecting true null hypotheses increases with the number of tests carried out. In other words, the larger the number of tests, the higher the likelihood of finding a significant impact on at least one outcome, even if the project did not have one in reality. This is referred to as Type I error, or "false positive". It is crucial to account for multiple hypothesis testing to mitigate the risk of making erroneous policy recommendations.[53] The issues relating to multiple hypothesis testing may arise when testing the significance of the impact of a single treatment on several outcome variables, when testing the impact of multiple treatments in a multi-arm setting, or during a combination of both.

Anderson (2008) provides a technical overview of the methods available to implement the two ways of controlling for multiple hypothesis testing. First, one can control the false discovery rate (i.e. the expected proportion of false positives [false rejections of the null] given a collection of statistical tests). Intuitively, this approach is appropriate in situations where the researcher is willing to accept some proportion of Type I error, typically when a large number of tests is carried out and the conclusion of a single test does not drive the overall policy recommendations. Second, one can focus instead on the family-wise error rate and control the likelihood of making at least one false rejection. Family-wise error rate corrections are more conservative than false discovery rate corrections and are more appropriate in situations with few tests, that is, a situation where each test would have a relatively high weight in the final policy recommendations, and hence a false rejection could be "very costly".

In the proposed IE, the analysis will focus essentially on testing a single hypothesis laid out in the main EQ presented in chapter IV:

EQ: Do the adaptive LHs promoted by the programme provide sustainable means of earnings?

In other words, there will be a large number of tests of the same hypothesis. Therefore, for the key indicators listed under the EQ in chapter IV, we propose to use false discovery rate corrections to adjust statistical inference. To do so, we will follow the two-step procedure developed by Benjamini, Krieger and Yekutieli (2006) – presented in Anderson (2008) – to adjust p-values and compute sharpened q-values to test the significance of ITT estimates obtained from regression specifications (1) and (3) (see VII.B, for details). In the analysis of heterogeneous effects by type of DW solution, in addition to adjusting p-values for individual tests (on the significance of β and δ in regression equation (4)), we propose to compute sharpened q-values to test the null that β and δ are not statistically different from each other.

5. QUANTILE TREATMENT EFFECT

The empirical framework presented so far puts the focus on average effects. One limitation of such analysis is that it does not provide insight into potentially heterogeneous treatment effects that may be relevant for policymakers. For instance, one could imagine that the LH intervention generates greater income gains for households that already experience high levels of income compared with others in their community. Maybe said households rank higher in the income distribution because they are more able or have better entrepreneurship skills than their lower-income counterparts, and this ability allows them to make the most of the offered training and input support. Conversely, we may

[53] Indeed, recommending an intervention that did not yield benefits would be very costly.

imagine larger gains from LH interventions for households that experience relatively low income levels, for instance if training and input support on adaptive LH enables them to unlock their untapped potential or simply removes existing barriers to entry for said income-generating activities (whereas higher-income households probably already had the means to overcome said barriers to entry, especially financial ones).

The estimation of quantile treatment effects (QTEs) is one possible way to measure whether causal impacts vary along with the distribution of the outcome variable.[54] Let Y be a random variable with the distribution function F_Y and $\tau \in [0, 1]$. Define the τ-quantile of F_Y, denoted by $q_Y(\tau)$ as:

$$q_Y(\tau) = F_Y^{-1}(\tau) = \inf\{y: F_Y(y) \geq \tau\}$$

Intuitively, the τ-quantile is the value of Y such that ($\tau \times 100$) per cent of observations have values below it. For instance, the median is the quantile that splits the sample into two equally sized parts. In other words, half the observations have a value of Y below the median. The latter is sometimes also referred to as the 0.5-quantile, the 50th quantile, the 50th percentile or Q50.

In the potential outcomes framework, let Y_1 and Y_0 be the values taken by outcome variable Y under treatment and control, respectively. The QTE can be expressed in a way analogous to the average treatment effect, whereby quantiles of the outcome variable are compared instead of means:

$$QTE(\tau) = q_{Y_1}(\tau) - q_{Y_0}(\tau)$$

The QTE depends on τ, and hence it may take different values at various points of the distribution, thereby allowing researchers to investigate potential heterogeneous treatment effects. In practice, thanks to randomization, the marginal distributions of Y_1 and Y_0 are identified by the realizations of Y observed in the treatment and control groups, respectively. Therefore, QTE(τ) can be estimated by a simple comparison of the sample τ-quantile of Y in the treatment group with the sample τ-quantile of Y in the control group. In practice, QTE(τ) as expressed above and its associated standard errors can be computed with a simple quantile regression (QR) at quantile τ of Y on the treatment variable.

While OLS-based regressions offer a straightforward framework to account for specific design features – namely stratified and clustered treatment assignment – this is not the case for QR.[55] For instance, in regression equation (1), stratification is simply accounted for through the inclusion of strata dummy variables.[56] Because the mean operator is linear – and thanks to the law of iterated expectations – OLS estimates of a variable's marginal effect on the conditional mean of the outcome are equal to that variable's effect on the unconditional mean of the outcome (i.e. the quantity of interest). Analogous to OLS, QR provides estimates of a variable's marginal effect on the conditional quantile of outcome Y. However, unlike the expectation operator, the quantile operator is not linear. Hence, as soon as covariates – for example, strata dummy variables – are included in QR, the estimated quantity becomes a conditional QTE and is not equivalent to the unconditional QTE.[57] While conditional QR can provide insightful results, unconditional effects are easier to interpret and more relevant for policymaking.

Therefore, we propose to use the unconditional quantile regression (UQR) estimator developed by Firpo, Fortin and Lemieux (2009), which allows the inclusion of covariates while recovering the effects on the unconditional quantiles of the outcome in a regression of the following form:

[54] Angrist and Pischke (2008) provide an introduction to QTE in chapter 7 of *Mostly Harmless Econometrics*.
[55] QR was introduced (some would say "revived") in the seminal paper by Koenker and Bassett (1978) and is discussed at length in Koenker and Hallock (2001). For a review of the uses of this technique in applied economics, see Davino, Furno and Vistocco (2013).
[56] Failure to account properly for stratification can lead to under-rejection of the null (Bruhn and McKenzie, 2009).
[57] Whereas conditional and unconditional QTEs are the same when the only regressor in the QR is the treatment variable.

$$Y_i = \alpha(\tau) + \beta(\tau)T_i + S_{upz}(\tau) + e_i(\tau) \quad (11)$$

Regression equation (11) is a simple rewrite of equation (1) in order to explicitly state that all the quantities estimated via QR or UQR depend on the quantile index τ, and hence may vary with different values of τ. In sum, estimating $\beta(\tau)$ via UQR should provide an unbiased estimate of the QTE at quantile τ. Because the UQR estimator consists of a two-step procedure, Firpo, Fortin and Lemieux (2009) recommend using a bootstrap procedure to compute standard errors, which can easily be adapted to re-sample blocks of data to account for within-cluster correlation of the error term arising from cluster-level randomization.[58] Randomization inference (see section VII.E.3) can potentially be used for any test statistic and hence provides yet another approach to correct inference for QTE in a stratified clustered RCT.

Finally, recall that quantiles are defined as the inverse of a variable's cumulative distribution function. As a consequence, (U)QR and QTE can only be estimated for continuous outcome variables. We propose to estimate the QTE for the following key outcome variables of interest: household total income; household total expenditure; income from adaptive LHs; sales and/or profits from income-generating activities. To provide a comprehensive overview of QTE along with the whole distribution, the quantile process will be estimated for $\tau = \{0.05, 0.10, \ldots, 0.95\}$ with a step of 0.05 (i.e. every fifth percentile from the 5th to the 95th percentiles).

[58] See Cameron, Gelbach and Miller (2008) for a discussion of "block bootstrap" procedures.

VIII. BASELINE SUMMARY STATISTICS

This chapter aims to present baseline values on outcomes of interest.[59] Section VIII.A presents insights into the data sources on which the summary statistics, presented in section VIII.B, are built.

A. BASELINE DATA

1. BASELINE CENSUS DATA

The baseline evidence relies on two waves of data collection: (1) a census, which also serves as a needs assessment for the programme, and (2) longer, more in-depth interviews with a subset of census respondents.

The main information on both data sources is presented in section VII.A.1. To recap, the census data, covering 66,171 households in the project area, were collected in January 2021. The rich data set includes information on the demographic background of household members, the socioeconomic status of households, access to DW, the household's food security situation, the household's exposure to natural disasters, and the respondent's perception of climate change. The questions were answered by a female household member knowledgeable on the listed topics.

While most sections were kept short, the census gathered detailed information on sociodemographic characteristics, which was not again collected during the baseline survey for two main reasons: (1) this information is not likely to change during such a short period, and (2) the duration of the extensive interviews conducted at baseline could be reduced; these interviews focused on collecting data on key indicators before the implementation of the project activities.

The census was used as a sampling frame from which to randomly select a baseline sample for in-depth structured interviews, which included 3,120 households eligible for the project. Section V.B.1 presents more detail on the sample size derivation, and information on the sampling can be found in section V.B.2.

2. BASELINE SURVEY DATA AND DATA COLLECTION

The baseline data were collected from a randomly selected sample of households from five upazilas,[60] divided into 39 UPs[61] targeted by the project. Households in 25 UPs participate in the project in Phase 1 and function as a treatment group, and households in the remaining 14 UPs get access to the intervention in Phase 2 and hence build the comparison group for the IE. A total of 3,120 households (80 households in each UP), of which 2,000 benefit from the intervention in Phase 1 and 1,120 benefit in Phase 2, were interviewed following a random selection from a census of all households. The households included in the baseline data were households identified as eligible for the programme.

During the baseline survey, enumerators administering the interviews asked the household member most knowledgeable about the household questions about the household's composition, asset ownership and access to finance, access to DW, income, and food consumption and expenditure.

Afterwards, the household's project beneficiary was asked questions about the household's food security, the income-generating activities she was involved in, her role in income decision-making, knowledge about climate change and adaptation to it, preparedness for natural disasters, social capital

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[59] Outcomes of interest for the underlying IE, assuming a time-lag of one year between project implementation in treatment and comparison areas.
[60] A subunit of a district, comparable to a county.
[61] The smallest rural administrative and local government unit. Each UP consists of nine wards, equal to a village.

and market access, and attitudes towards risk. If the female beneficiary was the person most knowledgeable about the household, she was asked to respond to all questions.

The baseline data collection was organized and executed by UNDP, deploying UNDP staff and project ward facilitators. To ensure high data quality, thorough training of enumerators was conducted before the onset of data collection. Ward facilitators, who took over the role of the enumerators and were responsible for the administration of interviews, participated in a two-day in-class training led by UNDP project staff. The in-class training started in mid-August and focused on detailed discussion of the questionnaire and the field protocols. It was followed by a one-day pilot test and a one-day debrief. UNDP project staff were present on the first day of data collection to monitor and support the data collectors. The training of enumerators and the launch of the data collection were implemented consecutively in each upazila.

A three-stage data quality assurance system was put in place by the project team during the data collection. As a first step, a trained supervisor performed spot checks during the field workday. Each supervisor was responsible for monitoring two to four enumerators at a time. The supervisors manually checked about 30 per cent of interviews conducted daily. Thereafter, the data were uploaded to the server, accessible to trained UNDP staff, who performed further quality checks in Excel. Here, particular attention was paid to inconsistencies within interviews (e.g. income versus expenditure of a household). Inconsistencies or ambiguities identified in either of the two steps were raised in a discussion with the enumerator who administered the interview. Enumerators followed up with respondents and shared all clarifications with the quality assurance staff.

After the completion of the baseline data collection, the project team shared all data with the LORTA team, who developed an ex post data quality check system to (1) thoroughly assess the quality of the collected data and (2) identify inconsistencies and queries in a way that complemented the data quality checks that were already performed during data collection. These inconsistencies and queries were then shared with the project team for further follow-up. All feedback from the project team has been incorporated into the data to ensure the baseline data are in optimal shape for the following analysis.

B. BASELINE SUMMARY STATISTICS

The summary statistics are based on data from the baseline census and the baseline survey and provide an overview of the situation before the project roll-out. Moreover, the summary statistics inform the IE strategy of the project by exploring potential differences between treatment and comparison groups. Following the design of the IE, the treatment group will receive project activities in Phase 1, starting after the baseline survey. The comparison group will benefit from the project in Phase 2, with implementation starting after the endline survey.

In the baseline survey, 3,120 households were interviewed, 2,000 households belonging to the treatment group and 1,120 households belonging to the comparison group. The summary statistics are based on a final sample of 3,104 households.[62] We present descriptive statistics for treatment and comparison households together with a comparison of these groups' characteristics. A statistical test (t-test) is used to determine if the differences between the groups for the characteristics are significantly different (Ali and Bhaskar, 2016). This allows us to assess the validity of the strategy to identify impacts by comparing groups that do not significantly differ in main characteristics before the project implementation.

[62] Sixteen observations were dropped after outlier trimming, following Crépon and others (2015) (see section VII.A.3).

1. BACKGROUND CHARACTERISTICS

Table 12~~Table 12~~ (see appendix) presents the summary statistics on the background characteristics of households sampled for the baseline survey, before project implementation. Of the treatment (comparison) households, 92.1 per cent (90.9 per cent) are male headed. The share of female-headed households is slightly lower than the Bangladeshi average, which was 15.8 per cent in 2018 (World Bank, 2018). The household head, on average, in treatment (comparison) households is 45 (46) years old and is married (93.8 per cent in treatment and 94.4 per cent in comparison households). Thirty-two per cent of household heads of treatment households and 29.4 per cent of household heads of comparison households are illiterate and have not received any formal education.

Even though the age of the household heads is statistically different, we do not assume it will constitute an important difference in reality, especially given that the absolute age difference only amounts to 1 year.

The average household size equals four household members, with an age-dependency ratio[63] of 54.7 per cent in treatment and 51.2 per cent in comparison households. This is slightly higher than the average age-dependency ratio of 47 per cent (World Bank, 2020). In 25 per cent (22.6 per cent) of treatment (comparison) households, at least one household member has a chronic illness, and at least one household member has a disability in 13.3 per cent (13.4 per cent) of treatment (comparison) households.

The most frequent income source in the last 12 months (i.e. the most common source among households) is transfers (77.8 per cent of both treatment and comparison households). This includes transfers from relatives and friends as well as transfers from (non-)governmental organizations and institutions. The second most common income source is livestock production, from which 62.4 per cent (55.2 per cent) of treatment (comparison) households drew income in the last 12 months.

Although transfers and livestock production are the most common income sources, these were the sources with the lowest average income amounts. Treatment (comparison) households that received transfers in the last 12 months received a total amount of BDT 7,570 (7,417). Treatment (comparison) households that earned income from livestock production in the last 12 months earned a total of BDT 6,347 (6,073) from this activity. The income source with the largest absolute amount of income generated in the last 12 months was non-agricultural wage employment (BDT 50,874 for treatment and BDT 39,652 for comparison households), in which 54.2 per cent (53.6 per cent) of treatment (comparison) households engaged. The amount that treatment households derived from non-agricultural wage employment is significantly higher than the amount comparison households earned from the respective source. Being aware of this imbalance will potentially allow us to control for it at the endline, following the strategies mentioned in section VII.E.1.

Looking into income shares in more detail, the data show that the main share of income in the last 12 months before the baseline survey was derived from non-agricultural wage employment (23.9 per cent for treatment and 21.4 per cent for comparison households), followed by income from non-farm household enterprises (21.3 per cent for both treatment and comparison households). Although livestock production was found to be the second most common activity (see section VIII.B.1), the income share derived from it is the lowest among the income sources (3.5 per cent for treatment and 3.3 per cent for comparison households).

Even though livestock production is not an activity that households derive a large share of income from, it is the income-generating activity that female respondents were involved in most in the last 12 months. Ninety-six per cent (93 per cent) of female respondents from treatment (comparison)

[63] The age dependency ratio is the ratio of dependents (individuals younger than 15 or older than 64 years) to the working age population (15–64 years) (World Bank Metadata Glossary).

households who were engaged in at least one activity produced livestock. In Bangladesh, women are primarily involved in livestock production and are mainly responsible for feeding and selling livestock products, especially if markets are distant (Mamun-ur-Rashid and Gao, 2012; Quisumbing and others, 2013), while men are mainly involved when dealing with larger animals or treating livestock in times of illness (Rahman, Ali and Hossain, 2008).

Fetching water is a female-dominated task too. In 77.6 per cent (74.2 per cent) of treatment (comparison) households only female members are involved in fetching water. In 5.3 per cent (7 per cent) of treatment (comparison) households only male household members are involved in fetching water.

In the Bangladeshi context, we differentiate between four main types of house, which differ in their durability. Most surveyed households (77.5 per cent of treatment and 75.2 per cent of comparison) live in a *katcha*, which is a temporary house, while 13.2 per cent (10.7 per cent) of households live in a *jhpuri*, equal to a shack. Of treatment (comparison) households, 7.9 per cent (12.1 per cent) live in a semi-permanent house, and 1.4 per cent (2.1 per cent) live in a permanent house, called a *pucca.*

About one fifth of treatment (comparison) households own agricultural land (22 per cent and 20.6 per cent, respectively). The average size of the agricultural land owned by treatment (comparison) households amounts to 24.880 (23.114) decimals. All households also own non-agricultural land.[64]

Bangladesh, and the project area in particular, is frequently hit by natural disasters and extreme weather events such as cyclones (Quadir and Iqbal, 2008). Of treatment (comparison) households, 35.1 per cent (40.1 per cent) indicated that their land had been affected by a natural disaster in the last 3 years, and 69.9 per cent (77.6 per cent) were able to fully recover their land, or even improve its situation, compared with the condition before the disaster. Moreover, a natural disaster affected 63.2 per cent (66.9 per cent) of the treatment (comparison) group's income sources, and the dwellings of 72.7 per cent (70.4 per cent) of the treatment (comparison) households were affected. Of treatment (comparison) households, 83.7 per cent (87.1 per cent) had been able to rebuild or even improve their dwelling after the disaster.

In the face of a natural disaster, 80.9 per cent (90.5%) of treatment (comparison) households have access to safe shelter. Almost all respondents stated that the household members can understand signals sent by EWS (97.9% treatment, 99.2% comparison) and know which steps to take after receiving EWS (97.1% treatment, 97.5% comparison). The statistical tests show that treatment households are significantly less likely to have access to safe shelter and to understand early warning signals in case of disaster.

Households follow different coping strategies in case costs are imposed by a natural disaster. Here, 7.5% (9.6%) of treatment (comparison) households save money to cope with costs. Households who do not opt for saving were asked which of the following means they rely on: 32.9% (31.4%) take up a loan, half of the households rely on support from relatives (50.1%) and 2.9% (2.5%) of households indicated to reduce food intake to cope with costs. 5.1% (4.0%) of treatment (comparison) households stated not to have any strategy to cope with the financial implications of a natural disaster.

Insurance policies are widely discussed as a tool to adapt to climate change (Thomas et al., 2011). Half of the respondents of treatment households (49.1%, and 45.2% respectively for comparison) indicated knowing what insurance is. In 12.3% (11.3%) of treatment (comparison) households at least one household member possesses insurance[65], while most households did not hold any insurance policy of any kind at the time of the baseline survey data collection. The main reasons for households

[64] This includes homestead land and open land in the courtyard, kitchen gardens, a pond or water body, government or khas land, and unused or fellow land.
[65] This includes life insurance, health insurance, house insurance, house endowment insurance and community insurance (e.g. self-help group).

not to have any insurance policy are the lack of knowledge about insurance (49.3% treatment, 53.5% comparison), the lack of monetary funds to purchase an insurance (23.3% treatment, 25.1% comparison) and the lack of trust in insurance companies (23% treatment, 21.2% comparison), while 13.6 per cent (12 per cent) of treatment (comparison) households do not believe in the need for insurance.

2. PROJECT ACTIVITIES, OUTPUTS, OUTCOMES AND IMPACTS

In the longer term, the described project activities, outputs and outcomes may impact the beneficiary's and beneficiary household's lives as defined in the ToC (see chapter III). Table 13~~Table 13~~ (see appendix) presents the summary statistics on project activities and anticipated outputs, as well as outcome and impact indicators of households included in the baseline survey, before project implementation.

The reactivation of old or the creation of new WLGs with project beneficiaries builds the basis for the success of the LH project component. As members of WLGs, beneficiaries will receive training on and inputs for the adoption of climate-adaptive LHs. Before implementation of the project, 13.6 per cent (5.5 per cent) of respondents from treatment (comparison) households were aware of WLGs existing in their communities. In 1.2 per cent (1.4 per cent) of treatment (comparison) households at least one female household member was a member of a WLG. While the membership of WLGs is very low at baseline, at least one female household member in 58 per cent (46.1 per cent) of treatment (comparison) households belongs to another community-based organization or group (see Table 12). Generally, this finding hints at a general openness of women to join groups and is promising for the success of beneficiaries joining the WLGs and receiving training and inputs through them. From a statistical point of view, we can say that, at baseline, significantly more female members of treatment households than comparison households were aware of existing WLGs and significantly more female members of treatment households already belonged to an organization or group. However, the difference in WLG membership, while statistically significant, is only marginally significant given that a low share of women were members.

At the baseline survey, 68.8 per cent (62 per cent) of respondents from treatment (comparison) households were aware of climate-adaptive LHs. The respondents' awareness of any of the eight project-promoted LHs was slightly lower (44.5 per cent treatment, 37.5 per cent comparison).

The rate of households in which any household member has ever participated in training on an adaptive LH is generally low, at 2.4 per cent (2.8 per cent) in treatment (comparison) households. At baseline, 81.1 per cent (79.9 per cent) of treatment (comparison) households already practise at least one climate-adaptive LH, and in 66.4 per cent (65.1 per cent) of these cases, this encompasses an LH promoted by the project.[66]

The beneficiaries' adoption of climate-adaptive LHs may have an impact on the household's income (see chapter III). Income information was collected for two reference periods at baseline: the last month and the last 12 months. The average household income in the last month amounted to BDT 8,394 (7,975) in treatment (comparison) households, which was about USD 98.67 (93.74) at the time of the baseline survey. [67] Respondents of treatment (comparison) households indicated that the household's income in the last 12 months came to BDT 115,523 (103,134), which was equal to USD 1,357.93 (1,212.30) . The balance tests detect statistical insignificance in the income in the last month (i.e. the treatment households had a significantly higher income than the comparison households). This might be driven by the income generated through non-agricultural wage labour, which was found

[66] Only households that identified the livelihoods promoted by the project as climate-adaptive ones are included in this statistic.
[67] The used exchange rate is the average exchange rate in 2021: USD 1 = BDT 85.073 (source: exchangerates.org.uk)

to be significantly higher for treatment households than for comparison households. During endline analysis, we will be able to control for this imbalance. No statistically significant differences are found in the income generated in the last month before the survey.

To put this in perspective, according to the latest Household Income and Expenditure Survey from 2016 (Government of Bangladesh, 2017), the average monthly income in rural areas was BDT 13,442. This would relate to an average yearly income of BDT 161,000 and, hence, a 39.3 per cent (56.1 per cent) higher yearly income than the income of the treatment (comparison) households.

That the project households' income is found to be lower than the average income of rural households in Bangladesh is in line with the project targeting poor households.

In addition to an income increase, the project intends to create income stability for participating households. In this study, income stability is approached through a measure of income diversification: the HHI, which equals the sum of the income shares for all income sources (see section VII.D.2 for details). We are presenting the inverse HHI, where the lower limit is 1, indicating no income diversification. There is no upper bound, and the higher the value, the higher the degree of income diversification. At baseline, the average inverse HHI was found to be 2.518 (2.483) for treatment (comparison) households. This will be compared with the endline value to see if income stability has increased.

To approximate household wealth aside from household income, a household asset index was created, following principal component analysis. This index is based on the assets presented in Table 11~~Table 11~~ in the appendix. At baseline, the index was found to be at –0.092 (0.17) for treatment (comparison) households; the statistically insignificant difference indicated that households from both groups exhibit the same level of wealth on average.

The total household expenditure[68] in the last 12 months, as reported by respondents at the time of the interview, was BDT 116,734 (104,919) in treatment (comparison) households, equal to USD 1,372.16 (1,233.28). We saw above that the annual income of the treatment households was significantly higher than that of the comparison households. Given the commonly close link between household income and expenditure, it does not come as a surprise that the annual household expenditure of treatment households is significantly higher than that of comparison households. This imbalance might be driven by the significant difference in household food expenditure in the week before the survey. We find that treatment households spent more on food than comparison households. In absolute terms, this difference amounts to BDT 123.92 (USD 1.45). Again, during the endline data analysis, we will be able to account for this imbalance (see section VII.E.1)

Moreover, comparing the average annual household expenditure to the average annual household income, we see that the expenditure exceeds the income on average by BDT 1,211 (1,785) for treatment (comparison) households. Loans and savings are not included in the income measure in this survey but contribute to a household's budget and to covering expenditures (United Nations, 2005). In the baseline data set, of the 61.2 per cent (62.4 per cent) of treatment (comparison) households for which expenditure exceeded income, more than half (69.2 per cent of treatment and 65.1 per cent of comparison households) had taken out a loan (see Table 12~~Table 12~~). Another explanation for the detected mismatch of expenditure and income may be the different recall periods used to collect the data.[69] The food expenditure was measured on a seven-day recall period and then extrapolated, which may lead to inaccuracies in the measure reported.

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[68] The total expenditure includes annual expenditure on education, clothing, health, communication, social costs, refreshments and miscellaneous items. In addition, an approximation of food costs was added, based on information respondents shared on weekly food costs.

[69] The income was measured on a monthly basis and then aggregated to the annual level. Food expenditure was measured on a weekly basis and then aggregated to the annual level. Other expenditures were measured on a yearly basis.

The household income is expected to be impacted by the female beneficiaries' participation in the project. An effect on the beneficiaries' decision-making status within the household is also intended. Through participation in LH training and the receipt of inputs for LHs, women will ideally adopt new LHs, engage (more) in income generation (and more without male household members), and have more decision-making power over the income generated and generally within the household. At baseline, 77.8 per cent (77.4 per cent) of female respondents had engaged in at least one income-generating activity in the last 12 months. The most common activity women had engaged in was livestock production, as presented in the background statistics. On average, female treatment (control) household respondents engaged in two (1.834 and 1.955, respectively) different income-generating activities. Before the project implementation, female treatment (control) household respondents engaged in 64 per cent (55.9 per cent) of income-generating activities alone or with another female household member, but without the engagement of a male household member. Female respondents from treatment households are significantly more likely than those from comparison households to engage in an income-generating activity alone or only with other female household members.

Female respondents were also asked how far they are involved[70] in decisions about how the income from their income-generating activity[71] is spent. The index ranges from 1 to 5, with 1 meaning that the respondent was not involved in any decision about spending of income from any income-generating activity she engaged in and 5 meaning that the respondent alone decided about spending the income from the income-generating activities she engaged in alone. The mean index for treatment (control) households lies at 3.354 (3.487) at baseline, indicating that a female respondent, on average, decided on how to spend half of the income herself.

Turning to more concrete examples of income-generating activity, 61.7 per cent (68.8 per cent) of treatment (comparison) respondents whose households had engaged in crop farming in the last 12 months had been involved in this income-generating activity, and 22.5 per cent (33.9 per cent) solely decided on how to spend the income generated from the activity. Of treatment (comparison) respondents whose households had engaged in fish, prawn or crab farming in the last 12 months, 28.3 per cent (37.9 per cent) had been engaged in this activity, and 12.8 per cent (16.7 per cent) solely made the decision on income spending.

In providing beneficiaries with adaptive and climate-adaptive means of income generation, one intended effect is the improvement of the households' food security status. Several widely used standardized tools exist to measure food security and its different components. The FCS is one of them and combines the aspects of dietary diversity and food frequency in one indicator (INDDEX Project, 2018). The FCS takes into consideration with which frequency a household consumed each of eight food groups[72] of interest in the last 7 days and weights the consumption according to the food group's nutrient density. The score ranges from 0 to 112, with a score up to 28 indicating poor consumption, a score higher than 28 but lower than 43 meaning borderline consumption, a score between 43 and 52 indicates acceptable low food consumption, and a score above 52 indicating acceptable high food consumption, in the Bangladeshi context (FSC, 2009).[73] The average FCS of treatment (comparison) households lies at 53.41 (52.51), which is slightly above the threshold for acceptable high food consumption. The food consumption of 51.8 per cent (47.2 per cent) of treatment (comparison) households is classified as acceptable high, while half of the sampled households have

[70] The involvement is classified as (1) not involved at all in decisions on how to spend income, (2) decides about some of income, (3) decides about half of the income, (4) decides about most of the income, (5) decides about all the income alone.
[71] This includes income from crop production; fish, prawn or crab production; livestock production; agricultural wage employment; non-agricultural wage employment; and work in the household's non-farm enterprise.
[72] The food groups (weights): main staples (2), pulses (3), vegetables (1), fruits (1), meat and fish (4), milk and milk products (4), sugar (0.5) and oil (0.5).
[73] The non-adjusted cut-offs define households with an FCS of 0–21 as poor, 21.5–35 as borderline and above 35 as acceptable. These thresholds were raised when analysing the FCS for the Bangladeshi context, and the acceptable FCS was split into acceptable low and acceptable high, to accommodate the standard local diet, in which fish and oil play an important role.

a lower FCS. This suggests a more severe food consumption situation among the project households than the Bangladeshi average. The Bangladesh Integrated Household Survey, a nationally representative survey, reported an average FCS of 66.7 in 2015 (IFPRI, 2015), which is 13.29 (14.19) higher than the average FCS in our sampled treatment (comparison) households.

Another common tool applied when dealing with food security, and particularly the sufficiency of household food intake, is the HFIAS. The HFIAS (Coates, Swindale and Bilinsky, 2007) is based on a set of nine questions,[74] grouped into three categories of food insecurity: (1) anxiety or uncertainty about the household food supply, (2) insufficient quality of food in terms of variety and preferences and (3) insufficient food intake and its physical consequences. The respondents share information on any of the nine scenarios covered by the questions that occurred in the last 30 days. From this, an indicator ranging from 0 to 27 is derived.[75] The average score for treatment (comparison) households lies at 2.476 (2.871). This result hints at a high level of household food security on average, as 0 equals secure food access and 27 indicates absolutely insecure food access.

However, the indicator needs to be interpreted with caution for various reasons. Firstly, the indicator only takes into consideration a recall period of 30 days, and the prevalence of food security is often seasonal (Hillbruner and Egan, 2008). Raihan and others (2018) found that households were less food insecure during the *post-aus* harvest period, during which the data collection took place, than they were in the *boro* harvest season.[76] Hence, the overall food security situation is likely worse than reflected in this indicator. Secondly, the questions asked are sensitive and might lead to misreporting on the side of the respondent and therefore to measurement errors. Nonetheless, the endline data will be collected at the same time of year from the same households and will therefore allow for a valid comparison of whether the food security situation has improved.

To shed more light on the household food insecurity situation, the collected data can be broken down into HFIAS categories. A household is defined to be severely food insecure if its members either often had to eat smaller or fewer meals in the past 30 days or faced at least once in the last 30 days a situation in which its members did not have any food available or at least one member had to go to sleep hungry or spend 24 hours without eating. Moderately food insecure households are often forced to eat a limited variety of foods or unwanted foods; mildly food insecure households sometimes experience these situations, and food secure households never do (Coates, Swindale and Bilinsky, 2007). Following the methodology and classification proposed in Coates, Swindale and Bilinsky (2007), we find that 27 per cent (25.9 per cent) of treatment (comparison) households are food secure, 44.8 per cent (37 per cent) are mildly food insecure, 23.6 per cent (28.6 per cent) are moderately food insecure and 4.6 per cent (8.6 per cent) are severely food insecure.

In addition to the LH component, one intended outcome of the project is to provide households with closer access to clean DW. At baseline, the water source of 10.1 per cent (12.1 per cent) of treatment (comparison) households was based on the household's compound, while the majority of households (53.5 per cent of treatment, 51 per cent of comparison) needed to walk up to 500 m to their water source. Of treatment (comparison) households, 18.2 per cent (19.4 per cent) lived up to 1,000 m away from their water source, and another 18.1 per cent (17.4 per cent) of households needed to walk a

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[74] The nine questions covered the following levels: (1) worry that their household would not have enough food, (2) not able to eat the kinds of foods preferred because of lack of resources, (3) eat a limited variety of foods due to a lack of resources, (4) eat some foods that they really did not want to eat because of lack of resources to obtain other types of food, (5) eat a smaller meal at breakfast, lunch or dinner than they felt they needed because there was not enough food, (6) eat fewer than three meals in a day because there was not enough food, (7) have no food to eat of any kind and no way to get more through purchases, from own garden or farm, or from storage, (8) go to sleep at night hungry because there is not enough food, (9) go a whole day and night without eating anything because there is not enough food.

[75] Each of the nine levels is scored from 0 to 3, with 0 meaning that the situation has not occured in the last 30 days, 1 meaning that the situation has occured rarely (once or twice), 2 meaning that the situation has occured sometimes (three to 10 times), and 3 meaning that the situation has occured often (more than 10 times).

[76] The post-aus harvest season lasts from September to October; the boro harvest season lasts from April to June.

distance of more than 1,000 m. On average, treatment (comparison) households spend more than 5.5 hours (5 hours) per week fetching water.[77] Respondents indicated that in 64.8 per cent (58.4 per cent) of treatment (comparison) households at least one household member had been affected by a waterborne disease in the 12 months before the data collection; this points to the need for access to cleaner DW.

Lastly, the project aims at improving the participating households' preparedness for a natural disaster by equipping the households with the means to engage in adaptive LHs. At baseline, 18.9 per cent (20.2 per cent) of treatment (comparison) household respondents indicated that, if needed after a natural disaster, the household members would have the technical skills to adopt a new LH. And while, on average, 86 per cent (81.7 per cent) of treatment (comparison) household members responded that they perceive their household as somewhat prepared against an extreme weather event, given the frequency of natural disasters in the project area and the intensity of effects on the households, equipping households with the means to adopt adaptive LHs seems to be promising in terms of positively impacting the beneficiary households' lives.

[77] The total time is compiled based on the sum of the average time needed to walk to the water source, the average time spent at the water source and the average time spent walking back home from the source, multiplied by how often a household member needs to go and fetch water per week.

IX. ETHICAL CONSIDERATIONS

The LORTA team is highly committed to following ethical principles in all stages of the research and data-collection process. To respect the do no harm principle, the LORTA team consults on an ongoing basis with local partners to ensure the ability of the research team to capture the complexity of the context and develop adapted approaches within the study design as well as the data collection.

The LORTA team engages early on with the project team to conduct a careful risk–benefit assessment, ensuring that risks to the study participants are minimized and that appropriate risk mitigation mechanisms are in place. As a complement to LORTA's do no harm policy, engaging early ensures respondents' safety and privacy and allows for anonymity to be maintained during the recruitment of and interviews with the participants. This engagement includes requesting support letters and authorization from local authorities to ensure that the data collection is conducted in a way that protects the rights, safety and dignity of research participants according to regulations prevailing in the study country.

The proposed IE design ensures that all study participants will benefit from the project (i.e. no participant will take part in the research study without participating in the project). The suggested phase-in design foresees that treatment households will participate in Phase 1, while the comparison households will do so in Phase 2.

X. CONCLUSIONS

In conclusion, the baseline findings based on data from 3,120 households indicate that the project and its activities are suitable for the targeted households.

The project aims to create closer access to clean DW for households, which will allow women – who are solely responsible for water fetching in the majority of surveyed households (77.6 per cent of treatment and 74.2 per cent of comparison households) – to reallocate time from fetching water towards (1) training on adaptive LHs and (2) income-generating activities promoted by the project. The endline analysis will shed light on the question of whether the time re-allocation was realized as anticipated. At baseline, on average, households spent 5.5 hours per week fetching water, given that the main water source for 89.9 per cent (87.9 per cent) of treatment (comparison) households was outside of the compound where they dwell.

The baseline results presented in chapter VIII show that the assumptions the ToC builds on (see chapter III), which can be back-checked using baseline data, are reasonable and that the project design seems to be well adapted to the local context.

At baseline, 77.8 per cent (77.4 per cent) of female respondents in treatment (comparison) households had engaged in at least one income-generating activity in the last 12 months, which suggests that women generally are allowed to engage in work and income generation, which is a prerequisite for the success of the project. We cannot make any statement as to why the remaining share of women did not engage in an income-generating activity but would hope that they would generally be allowed by their spouses and families to participate in the project's training and to take up the LHs promoted by the project.

Before the project implementation, the most common activity female respondents engaged in was livestock production. However, the income share derived from it was the lowest among income sources (3.5 per cent of the total annual income for treatment and 3.3 per cent for comparison households). Overall, the average household income in the last month amounted to BDT 8,394 (7,975) for treatment (comparison) households, which was about USD 105.02 (93.74) at the time of the baseline survey. This was BDT 5,048 (5,467) lower than the average income in rural areas of Bangladesh in 2016 according to data from the Household Income and Expenditure Survey (Government of Bangladesh, 2017).

At baseline, female respondents indicated that they decide how to use – on average – over half of the income generated by activities the respondents engaged in themselves. The endline analysis will shed light on whether the decision-making power of women has increased thanks to the project compared with the situation before the project implementation.

The income-generating activity contributing the biggest share to household income in the 12 months before project implementation was non-agricultural wage employment (23.9 per cent for treatment and 21.4 per cent for comparison households), followed by income from non-farm household enterprises (21.3 per cent for both treatment and comparison households). While these main income sources are not necessarily comparable to the income-generating activities promoted by the project, the baseline data hint at the general openness of households to adopt activities similar to the ones promoted by the project. At baseline, 81.1 per cent (79.9 per cent) of treatment (comparison) households already practise at least one climate-adaptive LH, and in 66.4 per cent (65.1 per cent) of these cases, this was an activity comparable to an LH promoted by the project. Hence, households are not only willing to engage in traditional activities but are open to climate-adaptive ones.

The share of surveyed households that had exposure to professional training before the project (2.4 per cent of treatment households), as well as the share of female respondents who were part of a WLG before the project (1.2 per cent of female respondents in treatment households), was very low.

However, in 58 per cent (46.1 per cent) of treatment (comparison) households, at least one female household member belongs to a community-based organization or group. This finding suggests that a general openness of women to join groups and is promising for the success of beneficiaries joining the WLGs and receiving training and inputs through them.

One main anticipated impact of the project on the beneficiary households' lives is the improvement of the household food security situation, which can be assessed at baseline through various indicators.

At baseline, the FCS was 53.41 (52.51) for treatment (comparison) households. The food consumption of 51.8 per cent (47.2 per cent) of treatment (comparison) households is classified as acceptable high, while half of the sampled households have lower than acceptable FCS. In addition, following the categories defined by the HFIAS, 27 per cent (25.9 per cent) of treatment (comparison) households are classified as food secure, 44.8 per cent (37 per cent) as mildly food insecure, 23.6 per cent (28.6 per cent) as moderately food insecure and 4.6 per cent (8.6 per cent) as severely food insecure.

The numbers are concerning in comparison not only to international levels but also to a national benchmark. Hence, the findings clearly show the beneficiaries' need for the intervention under evaluation, which aims to improve the household food security situation.

The project focuses not only on the proximity of water sources but also on the provision of clean DW. At baseline, 64.8 per cent (58.4 per cent) of treatment (comparison) household respondents indicated that at least one household member had been affected by a waterborne disease in the 12 months before the data collection, pointing to the need for access to cleaner DW.

The evaluation design, the balance tests, and the research conducted on whether treatment and comparison households are different in a systematic way using the baseline data, indicate that randomly sampled treatment and comparison groups are comparable on average, hence strengthening the evidence of successful randomization and giving credit to the evaluation strategy.

We detect imbalances in a small number of covariates, but some statistically significant differences in average characteristics between the treatment and control groups are expected to happen by chance, especially when balance tests are carried out on a large number of covariates. These imbalances do not mechanically invalidate the experimental design, nor do they systematically warrant adjusting the analysis. Imbalances only matter for covariates that are prognostic of the outcome variable (predictors) and can be controlled for. At the endline, we will follow the strategies as elaborated in section VII.E.1.

Overall, the descriptive baseline results also confirm the suitability and relevance of the project for the beneficiary population, and the endline analysis will be able to determine whether the anticipated project effects have been realized.

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APPENDIX

Table 10. Preliminary balance tests results

Variable	(1) TREATMENT N [Clusters]	(1) TREATMENT Mean (SE)	(2) CONTROL N [Clusters]	(2) CONTROL Mean (SE)	T-TEST DIFFERENCE (1) – (2)
Own (Who is the owner of this water source?)	42,667 [25]	0.159 (0.021)	23,218 [14]	0.173 (0.033)	–0.014
Own (Who is the owner of the land where you are residing?)	42,930 [25]	0.474 (0.018)	23,299 [14]	0.520 (0.037)	–0.046
Close (What is the distance between the drinking water source and your house?)	42,933 [25]	0.688 (0.036)	23,301 [14]	0.654 (0.049)	0.034
Yearly (How frequently does salinity happen here?)	27,007 [25]	0.803 (0.035)	15,607 [14]	0.780 (0.077)	0.023
Have you heard about the term "climate change"?	42,489 [25]	0.725 (0.033)	23,187 [14]	0.718 (0.063)	0.007
No disease in the last year (Health condition of the head of HH)	42,933 [25]	0.192 (0.026)	23,301 [14]	0.158 (0.022)	0.034
Do you have food stock at your home?	42,929 [25]	0.830 (0.026)	23,300 [14]	0.809 (0.023)	0.021
Do you make any savings to meet the treatment cost during a disaster?	42,821 [25]	0.192 (0.017)	23,279 [14]	0.211 (0.019)	–0.019
Average monthly income of the HH from various sources	42,933 [25]	8,798 (344)	23,301 [14]	9,303 (244)	–506
Agriculture/fishing day labour (Main source of income of the HH)	42,872 [25]	0.239 (0.021)	23,281 [14]	0.226 (0.030)	0.014
Do female members of the HH face difficulties in collecting water?	39,112 [25]	0.162 (0.022)	20,357 [14]	0.129 (0.020)	0.034
Are you or anyone in your HH a member of a safety net programme?	42,911 [25]	0.445 (0.038)	23,298 [14]	0.481 (0.075)	–0.036
Did you face difficulties in managing food for the HH members due to a disaster?	42,918 [25]	0.760 (0.023)	23,297 [14]	0.704 (0.026)	0.056
No. of people in the census at the union parishad level	42,933 [25]	2,501 (174)	23,301 [14]	2,382 (418)	120
F-test of joint significance (p-value)					0.280
F-test, number of observations					37,505

Notes: The value displayed for t-tests is the difference in means across groups. The value displayed for the F-test of joint significance is the p-value. SEs are adjusted for clustering at union parishad level and stratification on upazila. ***, **, and * indicate significance at the 1, 5, and 10 per cent critical level.

Abbreviations: HH = household; SE = standard error.

Table 11. Variables used in the construction of the asset-based wealth index

ASSET	SOURCE
Television	Baseline survey
Radio/two in one	Baseline survey
Refrigerator	Baseline survey
Bicycle	Baseline survey
Gola (small silo for paddy)	Baseline survey
Solar power	Baseline survey
Cell phone	Baseline survey
Water tank	Baseline survey
Almirah/wardrobe	Baseline survey
Bed (*khat*/*chouki*)	Baseline survey
Motorcycle	Baseline survey
Auto-rickshaw/easy bike	Baseline survey
Rickshaw/van	Baseline survey
Livestock	Baseline survey
Poultry	Baseline survey
Fishing net	Baseline survey
Boat	Baseline survey
Locally made motorized vehicle	Baseline survey
Power tiller	Baseline survey
Tractor	Baseline survey
Sewing machine	Baseline survey
Computer	Baseline survey
Fan	Baseline survey
Rice cooker	Baseline survey
Furniture	Baseline survey
Box	Baseline survey
Burner	Baseline survey
Cow	Census
Goat/sheep/pig	Census
Pond	Census
Hatchery	Census
Poultry farm	Census
House type: *jhpuri*	Census
House type: *katcha*	Census
House type: *semi-pucca*	Census
House type: *pucca*	Census
Toilet: no toilet	Census
Toilet: open pit/hanging/*katcha*	Census
Toilet: water sealed	Census
Toilet: flush toilet with septic tank	Census
DW source (dry season): tubewell	Census
DW source (dry season): motor	Census
DW source (dry season): PSF	Census
DW source (dry season): well-maintained pond	Census
DW source (dry season): non-maintained pond	Census
DW source (dry season): rainwater harvesting	Census
DW source (dry season): reverse osmosis	Census
DW source (dry season): tap	Census
DW source (dry season): no facility	Census

Asset	Source
DW source, ownership: own	Census
DW source, ownership: government	Census
DW source, ownership: NGO	Census
DW source, ownership: association	Census
DW source, ownership: other people	Census
DW source, distance to home: at the home compound	Census
DW source, distance to home: within 500 m	Census
DW source, distance to home: within 1,000 m	Census
DW source, distance to home: more than 1,000 m	Census
Ownership of land on which residing	Census

Abbreviations: DW = drinking water; NGO = non-governmental organization; PSF = pond sand filter.

Table 12. Baseline data: background characteristics

Variable	(1) Treatment N [Clusters]	Mean (SE)	(2) Control N [Clusters]	Mean (SE)	T-test Difference (1) – (2)
Characteristics of HH head					
Age (years)	1,993 [25]	45 (0)	1,111 [14]	46 (0)	–1**
Male (y/n)	1,993 [25]	0.921 (0.008)	1,111 [14]	0.909 (0.012)	0.012
Married (y/n)	1,993 [25]	0.938 (0.006)	1,111 [14]	0.944 (0.008)	–0.006
No education, illiterate (y/n)	1,962 [25]	0.320 (0.025)	1,092 [14]	0.294 (0.025)	0.026
Characteristics of HH					
Number of permanent HH members	1,993 [25]	4 (0)	1,111 [14]	4 (0)	0
HH dependency ratio	1,993 [25]	0.547 (0.018)	1,111 [14]	0.512 (0.021)	0.035
At least one HH member has a chronic illness	1,993 [25]	0.250 (0.015)	1,111 [14]	0.226 (0.026)	0.024
At least one HH member has a disability	1,993 [25]	0.133 (0.017)	1,111 [14]	0.134 (0.020)	–0.001
Any female HH member belongs to a community-based group (y/n)	1,993 [25]	0.580 (0.038)	1,111 [14]	0.461 (0.064)	0.119*
HH received income from transfers in the last 12 months (y/n)	1,993 [25]	0.778 (0.033)	1,109 [14]	0.778 (0.037)	0
Total amount of income received from transfers in the last 12 months	1,552 [25]	7,569.942 (888.937)	863 [14]	7,417.400 (960.398)	152.542
HH received income from livestock production in the last 12 months (y/n)	1,993 [25]	0.624 (0.033)	1,111 [14]	0.552 (0.076)	0.072
Total amount of income received from livestock production in the last 12 months	1,243 [25]	6,347.143 (583.031)	613 [14]	6,072.951 (664.743)	274.192
Respondent involved in livestock production in the last 12 months (y/n)	1,243 [25]	0.960 (0.010)	613 [14]	0.930 (0.029)	0.030
HH received income from non-agricultural wage employment in the last 12 months	1,993 [25]	0.542 (0.038)	1,111 [14]	0.536 (0.050)	0.006

Total income received from non-agricultural wage employment in the last 12 months	1,081 [25]	50,873.811 (4,109.883)	596 [14]	39,652.466 (4,369.515)	11,221.345**
Total annual HH expenditure exceeds total annual HH income (y/n)	1,993 [25]	0.612 (0.052)	1,111 [14]	0.624 (0.083)	–0.012
HHs whose expenditure exceeded the income did take up a loan (y/n)	1,219 [25]	0.692 (0.026)	693 [14]	0.651 (0.039)	0.042
Female HH members are solely responsible for fetching water (y/n)	1,734 [25]	0.776 (0.032)	884 [14]	0.742 (0.034)	0.034
Female and male HH members are responsible for fetching water (y/n)	1,734 [25]	0.171 (0.023)	884 [14]	0.188 (0.032)	–0.017
Male HH members are solely responsible for fetching water (y/n)	1,734 [25]	0.053 (0.020)	884 [14]	0.070 (0.023)	–0.017
Housing					
Type of house: *jhpuri* (shack) (y/n)	1,993 [25]	0.132 (0.014)	1,111 [14]	0.107 (0.015)	0.025
Type of house: *katcha* (temporary) (y/n)	1,993 [25]	0.775 (0.025)	1,111 [14]	0.752 (0.031)	0.023
Type of house: *semi-pucca* (semi-permanent) (y/n)	1,993 [25]	0.079 (0.014)	1,111 [14]	0.121 (0.033)	–0.042
Type of house: *pucca* (permanent) (y/n)	1,993 [25]	0.014 (0.004)	1,111 [14]	0.021 (0.007)	–0.007
Land ownership					
HH owns agricultural land (y/n)	1,993 [25]	0.220 (0.030)	1,111 [14]	0.206 (0.017)	0.014
Size of agricultural land (in decimals)	438 [25]	24.880 (2.798)	229 [14]	23.114 (2.654)	1.766
Exposure to a natural disaster					
HH's land affected by a natural disaster in the last 3 years (y/n)	1,992 [25]	0.351 (0.033)	1,111 [14]	0.401 (0.036)	–0.050
HH fully recovered/improved land (y/n)	700 [25]	0.699 (0.048)	446 [14]	0.776 (0.056)	–0.077
HH fully recovered/improved income source (y/n)	1,260 [25]	0 (.)	743 [14]	0 (.)	0
HH's dwelling affected by a natural disaster in the last 3 years (y/n)	1,993 [25]	0.727 (0.031)	1,111 [14]	0.704 (0.045)	0.023
HH fully recovered/improved dwelling (y/n)	1,671 [25]	0.837 (0.027)	961 [14]	0.871 (0.031)	–0.034

Coping strategies in event of a natural disaster					
HH members have access to safe shelter in case of natural disaster (y/n)	1,993 [25]	0.809 (0.036)	1,111 [14]	0.905 (0.029)	–0.095**
HH members understand early warning signals shared in case of disaster (y/n)	1,992 [25]	0.979 (0.006)	1,111 [14]	0.992 (0.003)	–0.013**
HH members know steps to be taken after receiving a warning signal (y/n)	1,950 [25]	0.971 (0.006)	1,101 [14]	0.975 (0.006)	–0.005
HH saves to cope with costs imposed by disaster (y/n)	1,988 [25]	0.075 (0.007)	1,110 [14]	0.096 (0.017)	–0.021
HH does not have a strategy to cope with costs imposed by disaster (y/n)	1,839 [25]	0.051 (0.014)	1,003 [14]	0.040 (0.007)	0.011
HH takes up a loan to cope with costs imposed by disaster (y/n)	1,839 [25]	0.328 (0.041)	1,003 [14]	0.314 (0.046)	0.014
HH gets support from relatives to cope with costs imposed by disaster (y/n)	1,839 [25]	0.500 (0.040)	1,003 [14]	0.501 (0.034)	–0.001
HH reduces food intake to cope with costs imposed by disaster (y/n)	1,839 [25]	0.029 (0.007)	1,003 [14]	0.025 (0.012)	0.004
Insurance					
Respondent knows what insurance is (y/n)	1,947 [25]	0.491 (0.051)	1,084 [14]	0.452 (0.059)	0.039
Any HH member possesses any insurance (y/n)	1,991 [25]	0.123 (0.021)	1,111 [14]	0.113 (0.022)	0.010
Reason for no insurance: lack of knowledge (y/n)	1,746 [25]	0.493 (0.051)	985 [14]	0.535 (0.053)	–0.042
Reason for no insurance: lack of money (y/n)	1,746 [25]	0.233 (0.045)	985 [14]	0.251 (0.058)	–0.018
Reason for no insurance: lack of trust in insurance companies (y/n)	1,746 [25]	0.230 (0.042)	985 [14]	0.212 (0.039)	0.018
Reason for no insurance: no need (y/n)	1,746 [25]	0.136 (0.028)	985 [14]	0.120 (0.034)	0.017

Notes: The table presents summary statistics, making use of 3,104 HH interviews. Sixteen interviews from the original sample were dropped, following the Crépon method of dealing with outliers (see section VII.A.3). SEs are adjusted for clustering at the union parishad level and stratification on upazila. Column (1) presents the number of treatment HHs and clusters; column (2) presents the union parishad-clustered means and respective SEs of the treatment HHs; column (3) presents the number of control HHs and clusters; column (4) presents the union parishad-clustered means and respective SEs of the control HHs; column (5) presents the value for t-tests, which are equal to the difference in means across the treatment and control groups.
***, **, and * indicate significance at the 1, 5, and 10 per cent critical level.

Abbreviations: HH = household; SE = standard error; y/n = yes/no.

Table 13. Baseline data: outcomes and impacts

Variable	(1) Treatment N [Clusters]	Mean (SE)	(2) Control N [Clusters]	Mean (SE)	T-test Difference (1) – (2)
Activities – creation/reactivation of WLG					
Respondent is aware of WLGs (y/n)	1,935 [25]	0.136 (0.033)	1,101 [14]	0.055 (0.023)	0.081**
Any female HH member is a member of a WLG (y/n)	1,935 [25]	0.012 (0.006)	1,101 [14]	0.014 (0.009)	–0.001
Output – awareness of and training on LH					
Respondent is aware of climate-adaptive LHs (y/n)	1,987 [25]	0.688 (0.059)	1,108 [14]	0.620 (0.088)	0.068
Respondent is aware of project-promoted adaptive LHs (y/n)	1,987 [25]	0.445 (0.067)	1,108 [14]	0.375 (0.076)	0.070
Any HH member has participated in training on adaptive LHs (y/n)	1,993 [25]	0.024 (0.007)	1,110 [14]	0.028 (0.013)	–0.004
Outcome – adoption of LH					
HH currently practises climate-adaptive LH (y/n)	1,366 [25]	0.811 (0.028)	687 [14]	0.799 (0.059)	0.012
HH practises homestead gardening (y/n)	1,378 [25]	0.663 (0.039)	734 [14]	0.639 (0.068)	0.024
Outcome – closer access to clean drinking water					
HH water source based on compound (y/n)	1,993 [25]	0.101 (0.019)	1,111 [14]	0.122 (0.034)	–0.020
Distance to HH water source: within 500 m (y/n)	1,993 [25]	0.535 (0.031)	1,111 [14]	0.510 (0.040)	0.025
Distance to HH water source: 501–1,000 m (y/n)	1,993 [25]	0.182 (0.017)	1,111 [14]	0.194 (0.018)	–0.012
Distance to HH water source: more than 1,000 m (y/n)	1,993 [25]	0.181 (0.031)	1,111 [14]	0.174 (0.038)	0.007
Time HH members spend fetching water per week (minutes)	1,590 [25]	338.651 (26.306)	832 [14]	304.391 (34.707)	34.260
At least one HH member was affected by waterborne disease in last the 12 months (y/n)	1,993 [25]	0.648 (0.046)	1,111 [14]	0.584 (0.056)	0.064
Impact – increase in HH income					
Total HH income last month (BDT)	1,993	8,393.870	1,111	7,975.041	418.830

	[25]	(387.816)	[14]	(642.265)	
Total HH income in the last 12 months (BDT)	1,993 [25]	115,523.574 (5,981.934)	1,111 [14]	103,134.387 (8,822.767)	12,389.186**
Inverse HHI	1,993 [25]	2.518 (0.066)	1,111 [14]	2.483 (0.074)	0.035
Share of HH income from crop production in the last 12 months	1,993 [25]	0.079 (0.018)	1,111 [14]	0.067 (0.017)	0.013
Share of HH income from crab production in the last 12 months	1,993 [25]	0.056 (0.006)	1,111 [14]	0.084 (0.011)	–0.028**
Share of HH income from livestock production in the last 12 months	1,993 [25]	0.035 (0.004)	1,111 [14]	0.033 (0.004)	0.003
Share of HH income from agricultural wage employment in the last 12 months	1,993 [25]	0.147 (0.016)	1,111 [14]	0.148 (0.017)	0.001
Share of HH income from non-agricultural wage employment in the last 12 months	1,993 [25]	0.239 (0.023)	1,111 [14]	0.214 (0.024)	0.025
Share of HH income from non-farm HH enterprises in the last 12 months	1,993 [25]	0.213 (0.014)	1,111 [14]	0.213 (0.017)	0
Share of HH income from transfers in the last 12 months	1,993 [25]	0.060 (0.005)	1,111 [14]	0.070 (0.007)	–0.010
Share of HH income from other sources in the last 12 months	1,993 [25]	0.171 (0.011)	1,111 [14]	0.172 (0.021)	–0.001
Total annual HH expenditure (BDT)	1,993 [25]	116,734.340 (6,023.095)	1,111 [14]	104,918.518 (9,039.734)	11,815.822*
Wealth index	1,993 [25]	–0.092 (0.160)	1,111 [14]	0.169 (0.211)	–0.261
Impact – improvement in women's status					
A woman has engaged in at least one income-generating activity in the last 12 months (y/n)	1,987 [25]	0.778 (0.030)	1,108 [14]	0.774 (0.050)	0.004
Number of different income-generating activities women engaged in in the last 12 months	1,546 [25]	1.834 (0.052)	858 [14]	1.955 (0.106)	–0.121
Share of income-generating activities respondent engages in alone or with other female HH member [0–1]	1,472 [25]	0.640 (0.042)	783 [14]	0.559 (0.052)	0.081**
Decision-making involvement index [1–5]	1,546 [25]	3.354 (0.103)	858 [14]	3.487 (0.145)	–0.133
Respondent involved in crop production in the last 12 months (y/n)	1,110 [25]	0.617 (0.052)	561 [14]	0.688 (0.054)	–0.071
Respondent solely decides on income from crop production (y/n)	685	0.225	386	0.339	–0.115

	[25]	(0.048)	[14]	(0.070)	
Respondent involved in fish/prawn/crab production in the last 12 months (y/n)	798 [25]	0.283 (0.041)	523 [14]	0.379 (0.078)	–0.095
Respondent solely decides on income from fish/prawn/crab production (y/n)	226 [25]	0.128 (0.032)	198 [14]	0.167 (0.023)	–0.038
Impact – improvement of HH food security					
FCS [0–112]	1,993 [25]	53.410 (0.947)	1,111 [14]	52.505 (1.401)	0.905
Acceptable high FCS (>52)	1,993 [25]	0.518 (0.034)	1,111 [14]	0.472 (0.049)	0.047
HDDS one-day recall [0–10]	1,993 [25]	7.175 (0.101)	1,111 [14]	7.087 (0.093)	0.088
High HDDS (7 or more food groups)	1,993 [25]	0.689 (0.029)	1,111 [14]	0.665 (0.027)	0.024
HFIAS [0–27]	1,993 [25]	2.476 (0.309)	1,111 [14]	2.871 (0.412)	–0.395
Food secure (y/n)	1,992 [25]	0.270 (0.053)	1,110 [14]	0.259 (0.068)	0.012
Mildly food insecure access (y/n)	1,992 [25]	0.448 (0.032)	1,110 [14]	0.370 (0.049)	0.07
Moderately food insecure access (y/n)	1,992 [25]	0.236 (0.036)	1,110 [14]	0.286 (0.055)	–0.049
Severely food insecure access (y/n)	1,992 [25]	0.046 (0.009)	1,110 [14]	0.086 (0.036)	–0.040
HH food expenditure last week (BDT)	1,993 [25]	1,205.526 (28.328)	1,111 [14]	1,081.604 (38.031)	123.922***
Impact – increase in HH preparedness for a natural disaster					
HH has the technical skill to adopt a new LH if needed after a disaster (y/n)	1,714 [25]	0.189 (0.026)	952 [14]	0.202 (0.039)	–0.013
Respondent perceives HH as (somewhat) prepared against extreme weather events	1,989 [25]	0.860 (0.033)	1,111 [14]	0.817 (0.051)	0.042

Notes: The table presents summary statistics, making use of 3,104 HH interviews. sixteen interviews from the original sample were dropped, following the Crépon method of dealing with outliers (see section VII.A.3). SEs are adjusted for clustering at the union parishad level and stratification on upazila. Column (1) presents the number of treatment HHs and clusters; column (2) presents the union parishad-clustered means and respective SEs of the treatment HHs; column (3) presents the number of control HHs and clusters; column (4) presents the union parishad-clustered means and respective SEs of the control HHs; column (5) presents the value for t-tests, which are equal to the difference in means across the treatment and control groups. ***, ** and * indicate significance at the 1, 5 and 10 per cent critical level.

Abbreviations: BDT = Bangladesh taka; FCS = Food Consumption Score; HDDS = Household Dietary Diversity Score; HFIAS = Household Food Insecurity Access Scale; HH = household; HHI =

Hirschman–Herfindahl Index; LH = livelihood; WLG = women livelihood group; y/n = yes/no.

Table 14. Detailed information on variables shown in appendix tables

Table in report	Variable label as displayed in a reported table	Type of variable or scale	Question text/comment	Source
Table 10	Own (Who is the owner of this water source?)	Binary	"Who is the owner of this water source?" Yes = 1 if own source, otherwise 0	Census
Table 10	Own (Who is the owner of the land where you are residing?)	Binary	"Who is the owner of the land where you are residing?" Yes = 1 if own land, otherwise 0	Census
Table 10	Close (What is the distance between the drinking water source and your house?)	Binary	"Main water source within 500 m from compound"	Census
Table 10	Yearly (How frequently does salinity happen here?)	Binary	"How frequently does salinity happen here?" Yes = 1 if yearly, otherwise 0	Census
Table 10	Have you heard about the term "climate change"?	Binary	"Have you heard about the term 'climate change'?"	Census
Table 10	No disease in the last year (Health condition of the head of HH)	Binary	"Health household head: no disease in the last year"	Census
Table 10	Do you have food stock at your home?	Binary	"Do you have food stock at your home?"	Census
Table 10	Do you make any savings to meet the treatment cost during a disaster?	Binary	"Do you make any savings to meet the treatment cost during a disaster?"	Census
Table 10	Average monthly income of the HH from various sources	Continuous	"Average monthly income of the household from various sources"	Census
Table 10	Agriculture/fishing day labour (Main source of income of the HH)	Binary	"Main source of income of the household" Yes = 1 if agriculture/fishing day labour is the main source, otherwise 0	Census
Table 10	Do female members of the HH face difficulties in collecting water?	Binary	"Do female members of the household face difficulties in collecting water?"	Census
Table 10	Are you or anyone in your HH a member of a safety net programme?	Binary	"Are you or anyone in your household a member of any safety net programme?"	Census
Table 10	Did you face difficulties in managing food for the HH members due to a disaster?	Binary	"Did you face difficulties in managing food for the household members due to a disaster?"	Census
Table 10	No. of people in the census at the union parishad level	Continuous	Constructed variable based on the union parishad assigned to each observation	Census
Table 12	Age (years)	Continuous	"Age (in years) of the household head"	Census
Table 12	Male (y/n)	Binary	"Sex of the household head"	Census

Table 12	Married (y/n)	Binary	Constructed variable based on the question “Marital status” Yes = 1 if married, otherwise 0	Census
Table 12	No education, illiterate (y/n)	Binary	Constructed variable based on the question “Education: Highest class passed” Yes = 1 if never been to school and cannot read and write, otherwise 0	Census
Table 12	Number of permanent HH members	Continuous	“Number of household members”	Census
Table 12	HH dependency ratio	Continuous	Constructed variable based on the number of household members and their age	Census
Table 12	At least one HH member has a chronic illness	Binary	Constructed variable based on “Is this member chronically ill?” Yes = 1 if at least one household member is chronically ill, otherwise 0	Census
Table 12	At least one HH member has a disability	Binary	Constructed variable based on the question “Is this member physically or mentally disabled?” Yes = 1 if at least one household member has a physical or mental disability, otherwise 0	Census
Table 12	Any female HH member belongs to a community-based group (y/n)	Binary	“Do you or any other female member of your household belong to any community-based organization or groups?”	Baseline
Table 12	HH received income from transfers in the last 12 months (y/n)	Binary	“Over the past 12 MONTHS, has your household had any income from transfers?”	Baseline
Table 12	Total amount of income received from transfers in the last 12 months	Continuous	“How much income did your household get from transfers in the LAST 12 MONTHS?”	Baseline
Table 12	HH received income from livestock production in the last 12 months (y/n)	Binary	“Over the past 12 MONTHS, has your household had any income from livestock?”	Baseline
Table 12	Total amount of income received from livestock production in the last 12 months	Continuous	“How much (in Taka) income did your household get from livestock in the LAST 12 MONTHS?”	Baseline
Table 12	Respondent involved in livestock production in the last 12 months (y/n)	Binary	“Over the past 12 MONTHS, have you been involved in your household’s livestock production?”	Baseline
Table 12	HH received income from non-agricultural wage employment in the last 12 months	Continuous	“Over the past 12 MONTHS, has your household had any income from wage employment in non-agricultural activities?”	Baseline
Table 12	Total income received from non-agricultural wage employment in the last 12 months	Continuous	“How much income did your household get from wage employment in non-agricultural activities in the LAST 12 MONTHS?”	Baseline
Table 12	Total annual HH expenditure exceeds total annual HH income (y/n)	Binary	Constructed variable based on the sum of all expenditures minus the sum of income from all applicable income sources over the last 12 months	Baseline

Table 12	HHs whose expenditure exceeded the income did take up a loan (y/n)	Binary	"Do you or any member of your household have taken any kind of loan/credit?"	Baseline
Table 12	Female HH members are solely responsible for fetching water (y/n)	Binary	Constructed variable based on the question "Who typically collects drinking water for the household during the dry season?"	Baseline
Table 12	Female and male HH members are responsible for fetching water (y/n)	Binary	Constructed variable based on the question "Who typically collects drinking water for the household during the dry season?"	Baseline
Table 12	Male HH members are solely responsible for fetching water (y/n)	Binary	Constructed variable based on the question "Who typically collects drinking water for the household during the dry season?"	Baseline
Table 12	Type of house: *jhpuri* (shack) (y/n)	Binary	Constructed variable based on information shared on "Type of house" Yes = 1 if a jhpuri (shack), otherwise 0	Census
Table 12	Type of house: *katcha* (temporary) (y/n)	Binary	Constructed variable based on information shared on "Type of house" Yes = 1 if a katcha (temporary), otherwise 0	Census
Table 12	Type of house: *semi-pucca* (semi-permanent) (y/n)	Binary	Constructed variable based on information shared on "Type of house" Yes = 1 if a semi-pucca (semi-permanent), otherwise 0	Census
Table 12	Type of house: *pucca* (permanent) (y/n)	Binary	Constructed variable based on information shared on "Type of house" Yes = 1 if a pucca (permanent), otherwise 0	Census
Table 12	HH owns agricultural land (y/n)	Binary	Constructed variable based on the question "Agricultural land (decimal)" Yes = 1 if size of land indicated greater than 0, otherwise 0	Census
Table 12	Size of agricultural land (in decimals)	Continuous	"Agricultural land (decimal)"	Census
Table 12	HH's land affected by a natural disaster in the last 3 years (y/n)	Binary	"Was any part of your land affected due to a natural disaster in the last 3 years (i.e. since 2018)?"	Baseline
Table 12	HH fully recovered/improved land (y/n)	Binary	Constructed variable based on the question "To what extent was the land recovered?" Yes = 1 if "recovered and better off" or "recovered to the same level", otherwise 0	Baseline
Table 12	HH fully recovered/improved income source (y/n)	Binary	Constructed variable based on the question "To what extent was the income source recovered?" Yes = 1 if "recovered and better off" or "recovered to the same level", otherwise 0	Baseline
Table 12	HH's dwelling affected by a natural disaster in the last 3 years (y/n)	Binary	"Was any part of your household's dwelling affected due to a natural disaster in the last 3 years (i.e. since 2018)?"	Baseline
Table 12	HH fully recovered/improved dwelling (y/n)	Binary	Constructed variable based on the question "To what extent was the dwelling recovered?"	Baseline

			Yes = 1 if "recovered and better off" or "recovered to the same level", otherwise 0	
Table 12	HH members have access to safe shelter in case of natural disaster (y/n)	Binary	"Is there any place to keep yourselves safe from any disaster? (shelter, communications)"	Census
Table 12	HH members understand early warning signals shared in case of disaster (y/n)	Binary	"Do you understand the early warning-related signals of disaster?"	Census
Table 12	HH members know steps to be taken after receiving a warning signal (y/n)	Binary	"Do you know about the steps that need to be taken after receiving signals of disaster?"	Census
Table 12	HH saves to cope with costs imposed by disaster (y/n)	Binary	"Do you make any savings to meet the treatment cost during a disaster?"	Census
Table 12	HH does not have a strategy to cope with costs imposed by disaster (y/n)	Binary	Constructed variable based on the question "If no [savings], how do you manage the cost of treatment?" Yes = 1 if no strategy, otherwise 0	Census
Table 12	HH takes up a loan to cope with costs imposed by disaster (y/n)	Binary	Constructed variable based on the question "If no [savings], how do you manage the cost of treatment?" Yes = 1 if taking up a loan, otherwise 0	Census
Table 12	HH gets support from relatives to cope with costs imposed by disaster (y/n)	Binary	Constructed variable based on the question "If no [savings], how do you manage the cost of treatment?" Yes = 1 if support from relatives, otherwise 0	Census
Table 12	HH reduces food intake to cope with costs imposed by disaster (y/n)	Binary	Constructed variable based on the question "If no [savings], how do you manage the cost of treatment?" Yes = 1 if the reduction in food intake, otherwise 0	Census
Table 12	Respondent knows what insurance is (y/n)	Binary	"Do you know what insurance is?"	Baseline
Table 12	Any HH member possesses any insurance (y/n)	Binary	"Does anyone in your household possess any insurance product?"	Baseline
Table 12	Reason for no insurance: lack of knowledge (y/n)	Binary	Constructed variable based on the question "[If no insurance product possessed by any household member] Why not?" Yes = 1 if the reason is lack of knowledge, otherwise 0	Baseline
Table 12	Reason for no insurance: lack of money (y/n)	Binary	Constructed variable based on the question "[If no insurance product possessed by any household member] Why not?" Yes = 1 if the reason is lack of money, otherwise 0	Baseline
Table 12	Reason for no insurance: lack of trust in insurance companies (y/n)	Binary	Constructed variable based on the question "[If no insurance product possessed by any household member] Why not?"	Baseline

			Yes = 1 if the reason is lack of trust in insurance companies, otherwise 0	
Table 12	Reason for no insurance: no need (y/n)	Binary	Constructed variable based on the question "[If no insurance product possessed by any household member] Why not?" Yes = 1 if the reason is no need for insurance, otherwise 0	Baseline
Table 13	Respondent is aware of WLGs (y/n)	Binary	"Are you aware of the existence of any Women Livelihood Group (WLG) in your community?"	Baseline
Table 13	Any female HH member is a member of a WLG (y/n)	Binary	"Are you or any other female member of your household currently a member of a Women Livelihood Group (WLG)?"	Baseline
Table 13	Respondent is aware climate-adaptive LH (y/n)	Binary	"Are you familiar with climate-adaptive livelihood options?"	Baseline
Table 13	Respondent is aware of project-promoted adaptive LHs (y/n)	Binary	Constructed variable based on the question "What climate-adaptive livelihood options do you know about?" Yes = 1 if the respondent is aware of at least one project-promoted activity, otherwise 0	Baseline
Table 13	Any HH member has participated in training on adaptive LHs (y/n)	Binary	Constructed variable based on "Have you received any training on climate-adaptive livelihoods?" and "Has any other member of your household received any training on climate-adaptive livelihoods?" Yes = 1 if either of the questions = yes, otherwise 0	Baseline
Table 13	HH currently practises climate-adaptive LH (y/n)	Binary	"Does your household currently practice any climate-adaptive livelihood options?"	Baseline
Table 13	HH practises homestead gardening (y/n)	Binary	Constructed variable based on the question "Please tell us what climate-adaptive livelihood options your household practices?" Yes = 1 if homestead gardening = yes, otherwise 0	Baseline
Table 13	HH water source based on compound (y/n)	Binary	Constructed variable based on the question "What is the distance between the drinking water source and your house in the dry season?" Yes = 1 if water source based on compound, otherwise 0	Census
Table 13	Distance to HH water source: within 500 m (y/n)	Binary	Constructed variable based on the question "What is the distance between the drinking water source and your house in the dry season?" Yes = 1 if water source based within 500 m, otherwise 0	Census
Table 13	Distance to HH water source: 501–1,000 m (y/n)	Binary	Constructed variable based on the question "What is the distance between the drinking water source and your house in the dry season?" Yes = 1 if water source based within 501–1,000 m, otherwise 0	Census

Table 13	Distance to HH water source: more than 1,000 m (y/n)	Binary	Constructed variable based on the question "What is the distance between the drinking water source and your house in the dry season?" Yes = 1 if the water source is based more than 1,000 m away, otherwise 0	Census
Table 13	Time HH members spend fetching water per week (minutes)	Continuous	Constructed variable equal to the sum of the responses shared on the following questions "How long does it take to walk to your main drinking water source?", "How long does one typically have to wait there?", "How long does it take to walk back from your main drinking water source?" multiplied by the information provided to the question "In a typical week during the dry season, how many times does your household need to go fetch water?"	Baseline
Table 13	At least one HH member was affected by a waterborne disease in last the 12 months (y/n)	Binary	Constructed variable based on the questions "Was any child under 5 in your household affected by water-borne diseases within last 12 months?", and "Was any child between 6 and 16 years old in your household affected by water-borne diseases within last 12 months?", "Was any adult (older than 16 years old) in your household affected by water-borne diseases within last 12 months?" Yes = 1 if any of the above questions = yes, otherwise 0	Baseline
Table 13	Total HH income last month (BDT)	Continuous	Constructed variable equal to the sum of income from all income sources in the last month	Baseline
Table 13	Total HH income in the last 12 months (BDT)	Continuous	Constructed variable equal to the sum of income from all income sources in the last 12 months	Baseline
Table 13	Inverse HHI	Continuous	Constructed variable based on shares of income from all income sources	Baseline
Table 13	Share of HH income from crop production in the last 12 months	Continuous	Constructed variable equal to income from specific income source in the last 12 months divided by total income in the last 12 months	Baseline
Table 13	Share of HH income from crab production in the last 12 months	Continuous	Constructed variable equal to income from specific income source in the last 12 months divided by total income in the last 12 months	Baseline
Table 13	Share of HH income from livestock production in the last 12 months	Continuous	Constructed variable equal to income from specific income source in the last 12 months divided by total income in the last 12 months	Baseline
Table 13	Share of HH income from agricultural wage employment in the last 12 months	Continuous	Constructed variable equal to income from specific income source in the last 12 months divided by total income in the last 12 months	Baseline
Table 13	Share of HH income from non-agricultural wage employment in the last 12 months	Continuous	Constructed variable equal to income from specific income source in the last 12 months divided by total income in the last 12 months	Baseline
Table 13	Share of HH income from non-farm HH enterprises in the last 12 months	Continuous	Constructed variable equal to income from specific income source in the last 12 months divided by total income in the last 12 months	Baseline

Table 13	Share of HH income from transfers in the last 12 months	Continuous	Constructed variable equal to income from specific income source in the last 12 months divided by total income in the last 12 months	Baseline
Table 13	Share of HH income from other sources in the last 12 months	Continuous	Constructed variable equal to income from specific income source in the last 12 months divided by total income in the last 12 months	Baseline
Table 13	Total annual HH expenditure (BDT)	Continuous	Constructed variable summing up all household expenditure in the last 12 months	Baseline
Table 13	Wealth index	Continuous	Constructed variable using principal component analysis based on variables presented in Table 11	Baseline
Table 13	FCS [0–112]	Discrete	Constructed variable ranging from 0 to 112 based on the frequency of intake of food from eight different food groups in the last 7 days, weighted according to the respective food groups' nutrient density	Baseline
Table 13	Acceptable high FCS (>52)	Binary	Constructed variable based on the FCS [0–112] variable Yes = 1 if "FCS [0–112]" greater than 52, otherwise 0	Baseline
Table 13	HDDS one-day recall [0–10]	Discrete	Constructed variable based on a one-day food recall of 10 different food groups	Baseline
Table 13	High HDDS (7 or more food groups)	Binary	Constructed variable based on the HDDS one-day recall [0–10] variable Yes = 1 if HDDS one-day recall equal to 7 or more, otherwise 0	Baseline
Table 13	HFIAS [0–27]	Discrete	Based on the following nine levels: (1) worry that their household would not have enough food, (2) not able to eat the kinds of foods preferred because of lack of resources, (3) eat a limited variety of foods due to a lack of resources, (4) eat some foods that they did not want to eat because of lack of resources to obtain other types of food, (5) eat a smaller meal at breakfast, lunch or dinner than they felt they needed because there was not enough food, (6) eat fewer than three meals in a day because there was not enough food, (7) have no food to eat of any kind and no way to get more through purchases, from own garden or farm, or from storage, (8) go to sleep at night hungry because there is not enough food, (9) go a whole day and night without eating anything because there is not enough food. Each of the nine levels is scored from 0 to 3, with 0 meaning that the situation has not occurred in the last 30 days, 1 meaning that the situation has occurred rarely (once or twice), 2 meaning that the situation has occurred sometimes (3–10 times) and 3 meaning that the situation has occurred often (more than 10 times).	Baseline
Table 13	Food secure (y/n)	Binary	Constructed variable based on "Eat a limited variety of foods due to a lack of resources" and "Eat some foods that they did not want to eat because of lack of resources to obtain other types of food"	Baseline

			Yes = 1 if never forced to eat a limited variety of food nor to eat unwanted foods, otherwise 0	
Table 13	Mildly food insecure access (y/n)	Binary	Constructed variable based on "Eat a limited variety of foods due to a lack of resources" and "Eat some foods that they did not want to eat because of lack of resources to obtain other types of food" Yes = 1 if either sometimes forced to eat a limited variety of food or unwanted foods, otherwise 0	Baseline
Table 13	Moderately food insecure access (y/n)	Binary	Constructed variable based on "Eat a limited variety of foods due to a lack of resources" and "Eat some foods that they did not want to eat because of lack of resources to obtain other types of food" Yes = 1 if either often forced to eat a limited variety of food or unwanted foods, otherwise 0	Baseline
Table 13	Severely food insecure access (y/n)	Binary	Constructed variable based on "Eat a smaller meal at breakfast, lunch or dinner than they felt they needed because there is not enough food", "Eat fewer than three meals in a day because there is not enough food", "Go to sleep at night hungry because there is not enough food" and "Go a whole day and night without eating anything because there is not enough food" Yes = 1 if either often had to eat smaller or fewer meals in the past 30 days or faced at least once in the last 30 days a situation in which the household did not have any food available, or at least one household member had to go to sleep hungry or spent 24 hours without eating, otherwise 0	Baseline
Table 13	HH food expenditure last week (BDT)	Continuous	Constructed variable equal to the sum of food expenditure on various food sources	Baseline
Table 13	A woman has engaged in at least one income-generating activity in the last 12 months (y/n)	Binary	Constructed variable based on the question "Over the past 12 MONTHS, have you been involved in your household's [income-generating activity]" Yes = 1 if at least one [income-generating activity] = yes, otherwise 0	Baseline
Table 13	Number of different income-generating activities women engaged in in the last 12 months	Continuous	Constructed variable based on the question "Over the past 12 MONTHS, have you been involved in your household's [income-generating activity]" for all respective activities	Baseline
Table 13	Share of income-generating activities respondent engages in alone or with other female HH member [0–1]	Discrete range 0–1	Constructed variable based on the question "Did you practice [income-generating activity] alone/with other female household members]?"	Baseline
Table 13	Decision-making involvement index [1–5]	Continuous	Constructed variable based on the question "Which of these statements reflects best the extent to which you could decide how the	Baseline

			income from [income-generating activity] over the past 12 months was spent/used?" for the respective activities	
Table 13	Respondent involved in crop production in the last 12 months (y/n)	Binary	"Over the past 12 MONTHS, have you been involved in your household's [income-generating activity]?"	Baseline
Table 13	Respondent solely decides on income from crop production (y/n)	Binary	"Over the past 12 MONTHS, have you been involved in your household's [income-generating activity]?"	Baseline
Table 13	Respondent involved in fish/prawn/crab production in the last 12 months (y/n)	Binary	"Over the past 12 MONTHS, have you been involved in your household's [income-generating activity]?"	Baseline
Table 13	Respondent solely decides on income from fish/prawn/crab production (y/n)	Binary	"Over the past 12 MONTHS, have you been involved in your household's [income-generating activity]?"	Baseline
Table 13	HH has the technical skill to adopt a new LH if needed after a disaster (y/n)	Binary	"Please tell us about your skill level in accepting a new livelihood option" Yes = 1 if technical skills = yes, otherwise 0	Census
Table 13	Respondent perceives HH as (somewhat) prepared against extreme weather events	Binary	"If an extreme weather event occurs in your village now, would you be prepared?"	Baseline

Abbreviations: BDT = Bangladesh taka; FCS = Food Consumption Score; HDDS = Household Dietary Diversity Score; HFIAS = Household Food Insecurity Access Scale; HH = household; HHI = Hirschman–Herfindahl Index; LH = livelihood; WLG = women livelihood group; y/n = yes/no.

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