School of Accounting, Economics and Finance

Three Essays on the Diffusion of Climate-smart Technology in Agriculture

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Declaration

To the best of my knowledge and belief, this thesis contains no material previously published by any other person except where due acknowledgement has been made. Neither does it contain any material which has been accepted for the award of any other degree or diploma in any university. This research is supported by an Australian Government Research Training Program (RTP) Scholarship.

Regarding human ethics (for projects involving human participants/tissue, and so on), the research presented and reported in this thesis was conducted in accordance with the National Health and Medical Research Council National Statement on Ethical Conduct in Human Research (2007) – updated March 2014. The proposed research study received human research ethics approval from the Curtin University Human Research Ethics Committee (EC00262), Approval Number # **HRE2021-0569**

The choice experiments conducted and reported in this research were registered at the American Economics Associations' registry for randomized control trials. The RCT ID is AEARCTR-0007829. This registration citation is as follows;

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Authorship Attribute Statements

The experimental designs and analytical frameworks in this research are prepared by the researcher. Professor Ruhul A. Salim and Dr Muhammad Habibur Rahman meticulously supervised each design and analysis.

Materials in Chapter 3 are presented in a conference, titled, 36th PhD Conference in Economics and Business 2022, UWA, Perth, WA, and the paper can be cited as follows:

Islam Z., Salim R., Rahman, M.H., (2022). Evaluating financial understanding in renewable agricultural technology adoption [Paper presentation]. 36th PhD Conference in Economics and Business 2022, UWA, Perth, WA.

Materials in Chapter 3, Chapter 4, and Chapter 5 will be used for journal article publications that will be co-authored by Dr. Muhammad Habibur Rahman and Professor. Ruhul A. Salim.

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Abstract

The net-zero target of reducing CO_2 globally by 2050, requires faster decarbonisation by upscaling climate-smart technologies. The diffusion of such technologies remains a challenge as providers do not consider potential adopters' heterogeneity in the targeting process. In this regard, the existing adoption literature does not sufficiently evaluate the intrinsic factors that differentiate climate-smart adopters from non-adopters. Motivated by these phenomena, this research examines three dispositions of irrigation users that any climate-smart technology upscaling strategy can utilize. Developing two choice experiments and following a natural experiment approach, this research evaluates the correlations between solar irrigation technology use and farmers' i) financial understanding, ii) pro-environmental behaviour, and iii) cooperation level. To conduct choice experiments and a face-to-face field survey, this research recruited 800 farmers in Bangladesh. Among 800 farmers, 400 use solar irrigation, and 400 use non-solar (diesel and electricity) irrigation.

This thesis comprises three essays. The first essay [Financial understanding of renewable technology adopters] evaluates the correlations between financial understanding and renewable agricultural technology adoption. Three parameters observe farmers' financial understanding, namely- i) financially forward-looking behaviour, ii) understanding of calculation and opportunity costs, and iii) risk-taking behaviour. Findings suggest that farmers using solar irrigation outperform in financial understanding and financial understanding improves with network intensity. Solar adopters are financially forward-looking and risk-takers. They also have a better understanding of calculations and opportunity costs. Solar adopters are more perceptive of the choice sets than non-adopters. An important takeaway is that

financial education through experienced adopters could be useful for upscaling adoption.

The second essay [Farmers' pro-environmental behaviour for renewable technology] examines- i) pro-environmental behaviour, ii) environmental motivations, and iii) the sensitivity of environmental motivations of solar adopters and non-adopters. The findings suggest that solar using farmers are pro-environmental irrespective of network intensity and they significantly differ from non-adopters who perceive that fossils cause damage while solar does not harm the environment. Farmers' pro-environmental behaviour is sensitive to overall sustainable practices (both on-farm and off-farm) and less related to perceptions or attitudes. Environmental motivations do not vary across energy sources. Farmers using solar for its environmental sustainability and easy management are less likely to save resources. The takeaway is that technology diffusion plan should include the promotion of and motivations for off-farm sustainable activities.

The third essay [Cooperation in a renewable irrigation entity] explores the impact of energy use on four novel cooperation dispositions, i.e., i) irrigation contract type, ii) irrigation group size, iii) irrigation proximity, and iv) irrigation efficiency. Findings suggest that solar irrigation positively influences the uptake of a crop contract, irrigation operations in a bigger group, and a larger irrigation length, and solar irrigation is economically efficient. Energy impacts vary across groups using the same pump and the same water source. Energy use also varies across various distances of pump and water source from land. The efficiency of irrigation in reducing cost and timing in solar irrigation use and such efficiency improves for a bigger solar user group with a history of contract change. Heterogeneity tests confirm variations of cooperation and efficiency across contract arrangements, equipment ownership, solar network intensity and water source. The takeaway is that long-term contract and management efficiency will increase cooperation for climate-smart technology.

The financial understanding experiment does not require any guidelines, payoff calculations, and answer correctness. This has significant implications for developing country energy consumers who lack formal education and training. Unlike the existing common behavioural experiments, understanding frame-sets in pro-environmental experiments does not require any sense of responsibility or mere perceptions, which may have caused biased responses previously. Variables measuring cooperation variables are beyond the previous lab and field experiments by exploring the structural or operational features of an entity. The analytical frameworks in this study have produced robust results. The future experimental approach may use farmers' dispositions evaluated in this research as intervention trials. The experimental designs and analytical frameworks can be replicated for any climate-smart technology diffusion and evaluation.

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Dedication

I dedicate this thesis to my respected professor Sanat Kumar Saha.

Contents

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List of acronyms

ANOVA	Analysis of Variance
BADC	Bangladesh Agricultural Development Corporation
BBS	Bangladesh Bureau of Statistics
BDT	Bangladeshi Taka (currency)
BMDA	*Barind* Multipurpose Development Authority
BPC	Bangladesh Petroleum Corporation
BREB	Bangladesh Rural Electrification Board
CPR	Common-pool Resources
CSA	Climate-smart agriculture
CO_2	Carbon dioxide
DCE	Discrete Choice Experiment
DTW	Deep Tube-well
GDP	Gross Domestic Product

GHGs	Greenhouse Gases
GOB	Government of Bangladesh
GOlogit	Generalized Ordered Logit
IDCOL	Infrastructure Development Company Limited
IPCC	Intergovernmental Panel on Climate Change
IRENA	International Renewable Energy Agency
IIA	Independence of Irrelevant Alternatives
Kwp	Kilowatt peak
LLP	Low Lift Pump
MNL	Multi-nomial Logit
MWp	Megawatt peak
NE	Natural Experiment
N_2O	Nitrous oxide
OLS	Ordinary Least Squares
Ologit	Ordered Logit
PES	Payment for Ecosystem Services
PV	Photovoltaic
RDA	Rural Development Academy
REN	Renewables Now
ROC	Receiver Operating Characteristic
SIP	Solar Irrigation Project
SREDA	Sustainable And Renewable Energy Development Authority
STW	Shallow Tube-well
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
UNEP	United Nations Environment Programme
WTA	Willingness-to-accept
WTP	Willingness-to-pay

Chapter 1

Introduction

1.1 Background and motivations

Agriculture has two complementary challenges, i.e., to ensure food security and to protect itself against climate change. By nature, agriculture needs climate and weather inputs and farmers adjust input decisions to these variables (Deschênes and Greenstone 2007). There are various environmental actions and one broad spectrum is climate-smart agriculture (CSA). Water-use efficiency, organic inputs, and climate-stress tolerant seeds retain the CSA focuses. Evidence of these practices is not conclusive about consistent adaptations. The existing *adaptation gaps* and resource constraints further increase the risks of climate change effects (IPCC, 2022; UNEP, 2022). Some methods are questionable because they remain chemical-intensive. Besides, CSA standards are unknown (Taylor, 2018). Identification of the right technologies is important for sustainable intensification to be efficient (Khanna and Miao, 2022). In this regard, for sustainable food systems, low-carbon and green-energy focused CSA could be a holistic climate action. Globally, the ongoing approach highlights that renewable energy is key to the *net-zero* target for 1.5°C scenarios. Wind and hydropower generation rose considerably in the early 21st century, while solar and bioenergy picked up shortly after the 2008-09 financial crisis (Arent et al., 2011). This approach had several loopholes. Renewable energy share accounts for only 10.4% of the total energy mix (REN21, 2018) and 26% of electricity (IRENA, 2022), indicating a sluggishly paced decarbonisation. A crucial reason might be that policies have not explored cost-effective market-based technologies. Besides, renewable energy supports often compete with fossil fuel and carbon pricing schemes (Gehlar et al, 2011;

Abrell et al, 2019). More importantly, policies do not sufficiently address agriculture's instant potential to accommodate renewable technologies.

The past evidence shows substantial economic and environmental gains of renewable technologies. Renewable energy uses on-site clean sources and mitigates fossils' impacts simultaneously. These technologies reduce CO_2 emissions, ensure inexhaustible and secure energy, slim energy bills, increase productivity, and empower local infrastructures (Alqahtani and Patiño-Echeverri, 2019; Sharma et al, 2021; Waheed et al, 2018; Yao et al., 2022; Felice et al., 2022; De Groote and Verboven, 2019; Kaya et al., 2019). Market performance of renewable technologies has improved and upscaling these technologies has become cost-effective (Arent et al., 2011)**.** Fixed installation cost has a decreasing trend and variable operation and maintenance costs are low in solar PV system (Closas and Rap, 2017) and wind stations (Pechak et al., 2011). Solar home systems became competitive with other traditional fuel sources (Lay et al., 2013). Lighting is cheaper in solar home panels than microgrids (Millingeret al., 2012). Consequently, renewable technologies made breakthroughs in the past decade. Macroeconomic performances, e.g., income and environmental indicators can drive renewable consumption further (Sadorsky, 2009; Salim and Rafiq, 2012; Lu et al., 2022)**.** However, users tend to have dilemmas about adoption decisions. They might consider the maturity or newness of a technology, timing of investments and the discounting factor (see De Groote and Verboven, 2019). The consequence is a low adoption rate and relevant evidence in favour of adoption is ambiguous. It is not only a matter of appropriate policy or technology efficacy but also a convergence of energy demand (of users) and supply (by providers). As endogenous models consider technology to be a key to growth, users' preference plays a big role in this convergence. Opting for renewable energy is a sustainable choice. Concerned and responsible users are likely to choose such technologies. However, in the case of agricultural technology, preference is also sensitive to natural and idiosyncratic contexts and may largely vary across farmers. Besides, farmers may or may not prefer renewable technology for its economic or ecological benefits entirely.

1.2 Energy use in agriculture and renewable technology contributions

Cereal crops (Li et al., 2019; Zhen et al., 2018), cropping method (Felkner et al., 2009; Zou et al., 2015), and land use (Calvin et al., 2016; Pagani et al., 2017) do not necessarily follow a sustainable approach. Inputs invariably use direct and indirect energy based on sources and still the energy efficiency is low. Chemical inputs and machinery consume higher amounts of energy than they yield (Pagani et al., 2017; Soni et al., 2013). Nutrient contents of chemical inputs and machine features including operating time determine energy intensity. For example, if crops require irrigation either supplementary or intensive, energy consumption increases. Among all farm operations, irrigation is a complex activity on which crop yield quality and quantity mostly depend. It involves several periodic processes (i.e., a long gestation period) and requires a substantial amount of water and electricity. The use of electricity and water varies with machines and water sources for pumping, vehicles for water transportation, and finally equipment for installations (Zou et al., 2015). These processes generally consume a large volume of electricity. Irrigation also allows land to leach fertilizers and water evaporation that discharge N_2O and CO_2 (Soni et al., 2013). Both energy intensity and emissions vary across farming operations, even in the irrigation process alone. In such cases, altering crop choice or land use may not be a feasible solution. Increasing afforestation would be more catastrophic in developing countries where land uses have already constrained the existing food production. The net benefit would increase if inputs were economically, socially, and environmentally cost-effective. In this regard, food systems require a paradigm shift and renewable technology is a pragmatic decision.

The advocates of the water-energy-food (WEF) nexus argue that renewable technology improves resource security in all three subsystems simultaneously (Feng et al., 2014; Terrapon-Pfaff et al., 2018; Gao et al., 2013). These studies mostly found comprehensive benefits of water-use efficiency and increase in crop yield and farmers' income. However, not all renewable sources are equally beneficial for agriculture. Solar and wind are largely reliable unlimited sources while hydropower and bioenergy involve adverse impacts (Terrapon-Pfaff et al., 2018). Hydropower causes water concerns and bio-energy could increase land competition between food and energy crops. As evidence suggests, solar energy has the advantages of- i) providing a larger technology life (25 years approximately); ii) using less labour; and iii) competing equipment costs using alternative energy. Renewable technology is a *mechanized-labour solution* to labour shortages (Hamilton et al., 2022). Thus, the usefulness of a specific renewable technology should motivate its adoption.

1.3 Farmers' heterogeneity in technology adoption: problem statement

In agriculture, mostly input-price sensitivity determines cropping technology as well as cropping (Asher and Novosad, 2020). That means a technology improving yields and input efficiency guides adoption decisions generally. According to the IPCC (2014) report, only land and soil management is cost-effective, and yet farmers overuse chemicals. As Bovenberg and Smulders (1995) argued, environmental quality should perform both *utility* and *productive* roles, renewable technology adoption cannot rely only on its economic cost-benefit decisions. Given the climate variables' volatility, a production function approach (i.e., input cost-yield gain linkages) becomes ambiguous if the approach misses out on the factors of farmers' decision-making process (Deschênes and Greenstone, 2007). In addition, if potential adopters only consider and compare the marginal costs of alternatives, they might underestimate future environmental costs (Joskow, 2011). Thus, farmers' technology adoption decisions may follow a complex utility maximization subject to internal and external factors.

The extant literature on farm-level technology adoption evaluates the factors determining technology use and identifies barriers, i.e., own financial constraints, credit inaccessibility, insufficient subsidy, and low human capital (e.g., Flory, 2018; Mukherjee, 2020; Salazar et al., 2019; Van Campenhout et al., 2021). In human capital, knowledge facilitates adoption, and learning by doing is an embraced strategy in this process. Particularly in renewable energy cases, knowledge through its spillover processes (e.g., output, investment, technology) reduces policy costs (Bretschger et al., 2017). Their study showed that such impacts in agriculture are less convincing than in the transportation, manufacturing, and power sectors. It is not surprising because knowledge receivers in these sectors are different and so are their capabilities of knowledge processing. Besides, rural areas often have robust constraints in top-down (policy) and bottom-up (adoption) methods. For example, energy insecurity is severe in villages due to low or no grid connections and system inefficiencies (Amin et al, 2022). Renewable energy has the largest potential in rural areas to ensure energy security. However, if the identification of potential users is one of the adoption conditions, users' dispositions are crucial. Any problematic selection produces the worst adoption outcomes (Balew et al., 2022). Lack of coordination between the extension departments and local communities is one possible reason behind this inefficiency. The agricultural record is not yet structured and complete in many developing countries. Often in sustainable projects, providers (of technology or any complementary services) do not consider farmers' heterogeneity in perceptions and actions (on-farm and off-farm). Extension methods cannot be effective in sustainable solutions unless local communities perceive them. Farmers may or may not use external information. If thoughtful behaviour is a *self-control* attitude (Kaiser and Menkhoff, 2022), adopters find technology values based on their dispositions. Individual cognition is a threshold to understanding technology values and sustainable users may retain a higher threshold.

Theoretically, technology is either information or knowledge in growth models and none of these existing models has theorized the characteristics of technology adopters. Based on the overview above, this research finds three major gaps in the existing literature. Firstly, most sustainable literature evaluated farmers' heterogeneity from their responses about technology impacts only. Adoption studies in this genre also largely focus on the supply side, e.g., resource constraints and accessibility and the factors determining technology adoption. Secondly and precisely, renewable energy evidence remains predominantly building-oriented, e.g., solar home systems. Finally and most importantly, the available evidence of technology adoption did not evaluate the embodied factors that differentiate climate-smart adopters from non-adopters.

1.4 Research objectives and thesis organization

This research evaluates farmers' dispositions that can elicit their decisions on renewable technology use. Specifically, it examines three dispositions, namely financial understanding, pro-environmental behaviour, and cooperation. Thus, this thesis comprises three essays on these dispositions. The organization of this thesis continues as follows. Chapter 2 presents the scenarios of the study area and the selection process of the study area and a sample of farm-households. This chapter also gives a full account of sample characteristics. Then Chapters 3, 4, and 5 provide the problem statements, reviews of literature, experimental designs, empirical strategies, findings and interpretation of the three essays of this research respectively. Finally, Chapter 6 discusses a summary of findings, and policy suggestions and concludes this thesis with some light on further research possibilities.

The first essay ‘Financial understanding of renewable technology adopters’ evaluates the correlations between financial understanding and renewable agricultural technology adoption. Three parameters observe farmers’ financial understanding, namely- i) financially forward-looking behaviour, ii) understanding of calculation and opportunity costs, and iii) risk-taking behaviour. To estimate the probability of each parameter this study develops mutually exclusive discrete choices based on the risk-return profiles. Overall findings suggest that farmers using solar irrigation outperform in financial understanding and financial understanding improves with network intensity. Solar adopters are financially forward-looking and risk-takers. They also have a better understanding of calculations and opportunity costs. Regarding the experimental design, the visibility of choice sets impacts farmers’ calculation ability, and the risk-taking level varies with choice constructions. Solar adopters are more perceptive of the choice sets than non-adopters. An important takeaway of this study is that financial education through experienced adopters could be useful for upscaling adoption.

The second essay ‘Farmers’ pro-environmental behaviour for renewable technology’ examines- i) pro-environmental behaviour, ii) environmental motivations, and iii) the sensitivity of environmental motivations of solar adopters and non-adopters. The choice experimental design uses competitive frames to examine these three behaviour aspects. The findings in this study suggest that solar user-farmers are pro-environmental and they significantly differ from non-adopters who perceive that fossils cause damage while solar does not harm the environment. Farmers' pro-environmental behaviour is sensitive to overall sustainable practices (both on-farm and off-farm) and less related to perceptions. Environmental motivations do not vary across energy sources and results are robust for farmers who intend to save resources, farmers who intend to control resource loss, and even farmers who switch between saving and loss control. Thus, there is no framing effect on energy use. Farmers using solar for its environmental sustainability and easy management are less likely to save resources. Farmers' pro-environmental behaviour and motivations are less likely to be influenced by solar network intensity. Solar use for its economic efficiency influences the switch between resource saving and loss control. The key takeaway of this part is that technology diffusion plan should include the promotion of and motivations for off-farm sustainable activities.

The third essay 'Cooperation in a renewable irrigation entity' explores the impact of energy use on four cooperation dispositions for i) irrigation contract type, ii) irrigation group size, iii) irrigation proximity, and iv) irrigation efficiency. The methodology follows a natural experiment approach and employs logit, mean regression, median regression, and instrumental variable regression processes for estimation. Findings in this part suggest that solar irrigation positively influences the uptake of a crop contract, irrigation operations in a bigger group, and a larger irrigation length, and solar irrigation is economically efficient. The quantile regression process suggests that energy impacts vary across groups using the same pump and the same water source. Energy use also varies across various distances of pump and water source from land. This study finds the economic efficiency of irrigation in reducing cost and timing in solar irrigation use and such efficiency improves through larger cooperation in terms of a bigger irrigation group. Robustness and heterogeneity tests confirm variations of cooperation and efficiency across contract types, irrigation equipment ownership, water source, and solar network intensity. The takeaway is that long-term contract and management efficiency will increase cooperation for climate-smart technology.

1.5 Significance of this research

The net-zero target is to reduce 20 G tonnes of CO_2 globally by 2050 and renewable technologies would help reduce 25% of this amount (IRENA, 2022). To achieve this target, external finance and technology support and internal resources should be mobilized together. Various reports of NDCs (Nationally Determined Contributions) suggest that upscaling remains a challenge as institutions lack appropriate approaches for implementation. Even if local communities receive direct finance, technology supply, and capacity-building support, an appropriate targeting method is deemed necessary. In particular, while selecting farmers for climate-smart technology use, providers neither evaluate nor utilize any relevant behavioural characteristics or operational preferences. The networking between providers and users can be useful. Factors for each user and that at the community level are more effective to identify how to approach potential users and whom to approach. Conceptually, this research emphasizes users' identification process to induce renewable technology adoption and its faster diffusion. Technology upscaling strategies can utilize users' dispositions. As per methodology, this research uses two novel choice experiments to evaluate farmers' financial and environmental behaviours and employs a natural experiment approach that uniquely explores farmers' cooperation in technology choice. This research focuses on irrigation energy technology. It is a suitable context because any perception spill-over is usual among farmers using the same irrigation source and yet technology is either an individual or a collective choice. Thus, a microanalysis of farm-households allows elucidation of the correlations between irrigation technology choice and farmers' dispositions. Specifically, financial and environmental behaviour identify solar and non-solar adopters at the farmer level, while cooperation variables indicate technology efficiency at the community level.

The first essay makes the following contributions to sustainable adoption literature. It develops a new choice experimental design to show that technology adoption predicts financial understanding. Like the existing financial literacy literature, this approach does not require- any learning/information guideline, multi-period payoff calculations, and answer correctness, to observe financial understanding. This has significant implications for a developing country's energy consumers who lack formal education and training. This study is also important for energy transition planning. Findings suggest that financial education and investment experience are useful for increasing sustainable technology adoption. Thus, institutions can use experienced adopters to improve the financial understanding of potential users.

The second essay adds insights to the literature on the environmental framework for sustainable practices. This study uses competing frame sets and empirical processes that reflect farmers' environmental behaviour oriented largely by actual practices. Unlike the existing common behavioural methods, understanding frame-sets in choice experiments in this study does not require any (negative or positive) sense of responsibility, mere perceptions or intuitions, which may have caused biased responses previously. Thus, institutional approaches to motivate sustainable uptake can utilize similar frames. In the empirical processes, various cohorts' comparisons help evaluate the factors influencing the consistency of motivations. Local extension services could focus on these factors, e.g., off-farm sustainable activities, post-harvest management, perceptions of alternative technologies, and so on.

The third essay makes significant contributions to collective action literature, especially on farming. Firstly, this study looks into the nature of conditional and embedded cooperation employing a natural experiment approach. Secondly, this study explores three new cooperation indicators in farming operations, i.e., contract/payment arrangements, group, and length of irrigation. Thirdly, regression processes help discover cooperation variations in these respects and by technology adoption intensity. Fourthly, this analysis emphasizes the efficiency of cooperation in irrigation management (i.e., irrigation contracts and payments, irrigation group size, irrigation length, irrigation frequency and timing) that are not limited to cost-efficiency.

Chapter 2

Study area description and sample characteristics

2.1 Introduction

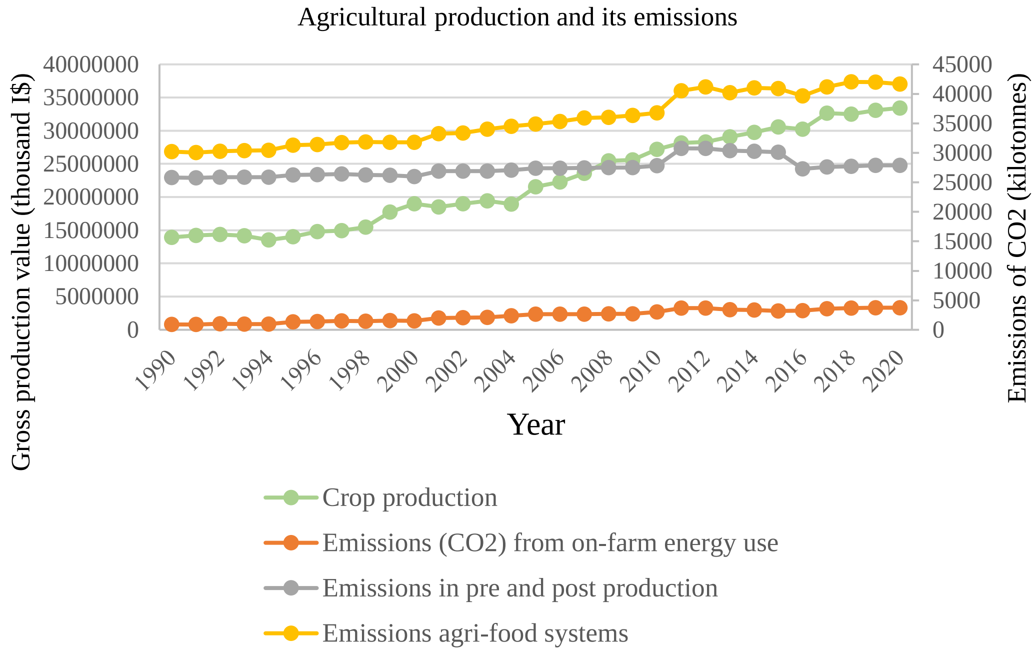
This chapter focuses on the profile of the study area and the characteristics of the sample (i.e., farming households). The specific objectives of this chapter are- a) to explore solar irrigation potential; b) to understand the mechanism of solar irrigation systems; and c) to explain the selection process of the study area and sample households. The profile of the study area includes an agricultural profile focusing on water and energy sources and the solar irrigation situation in Bangladesh. Sample characteristics include all variables to describe the sample's socio-demographic characteristics, farm and cultivation features, institutional accessibility profiles, and irrigation profiles. This chapter explains the sampling frame and the selection process of the study area and the study households. The unit of analysis is farming households and the analysis uses farm-household level characteristics from a primary survey with a structured questionnaire. The remaining sections proceed as follows. Section 2.2 describes the agricultural production scenario, emissions from agriculture, irrigation modes, and solar irrigation systems in Bangladesh. Section 2.3 discusses the selection process of the study area and sample households. Section 2.4 illustrates the descriptive statistics of all variables for the characteristics of farming households in the study area. Section 2.5 presents the research framework including the coordination matrix. This chapter concludes with a chapter summary.

2.2 Agriculture and solar irrigation in Bangladesh

Bangladesh is an agricultural resource-dependent country. According to the *Yearbook of Agricultural Statistics, 2021*, agriculture's share in GDP was 13.63% and its employment amounted to 40% approximately (BBS, 2022). The report also records that an amount of 38693000 MT of major cereal crops including rice, wheat, and maize was cultivated in 12029542.70 (12.03 million) hectares of land in 2019-20. Because of soil topography and water network, it has three cropping seasons, *Rabi* (mid-November to mid-March), *Kharif*-I (mid-March to mid-July), and *Kharif*-II (mid-July to mid-November). That is why the country has a high cropping intensity[1] of 198% and there are mostly double-cropped areas. However, following the Green Revolution in the 1960s, the country mostly cultivated high-yielding crops and used intensive farming technologies. Alauddin et al. (2021) analysed Conway's sustainability hypothesis for rice yields and observed that the country could maintain sustainably high yields. Accordingly, the following Figure 2.1.a shows an increasing trend in crop production value for the period of 1990-2020. The emission factor in agro-food systems shows the same increasing pattern. In addition, emissions in the pre- and post-production phases have been steadily high during this period. Emissions from on-farm energy use have been considerably lower than the levels of emissions in different production phases and total emissions from agriculture. However, energy use has accelerated in the last decade and emissions increased accordingly. In this regard, intensive farming technologies are responsible for cultivation methods to be ecologically unsustainable (Alauddin et al., 2021). In addition, a larger variability in climate parameters makes agricultural production vulnerable to climate change and its effects. Changes in rainfall and temperature increase the variability of rice yield during monsoon, while they reduce the variability in dry seasons (Sarker et al., 2014). This implies that intensive irrigation in dry periods is saving crops and supplementary

[1] The cropping intensity is the percentage of gross cropped area divided by net-cropped area. Gross cropped area includes fours cropping patterns, namely single, double, triple, and quadruple.

irrigation is necessary during monsoon. Thus, on-farm energy use increases annually and there is further stress on water sources.



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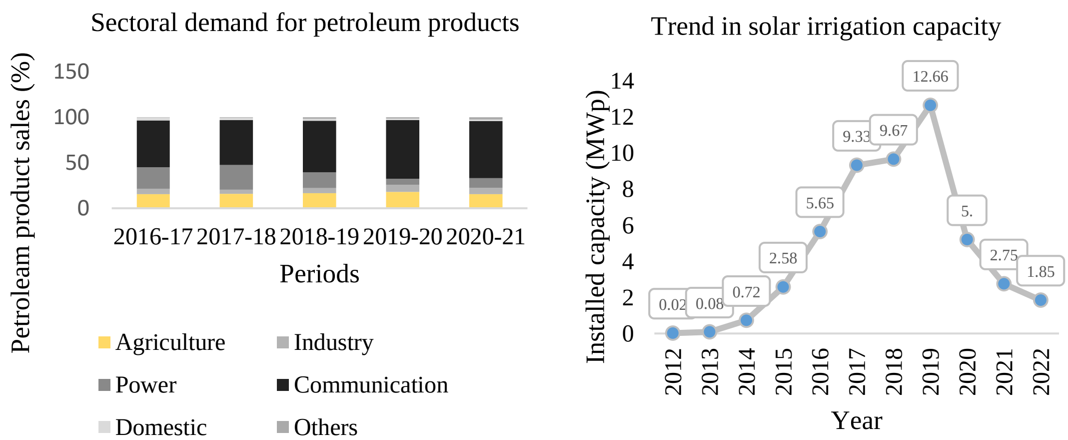
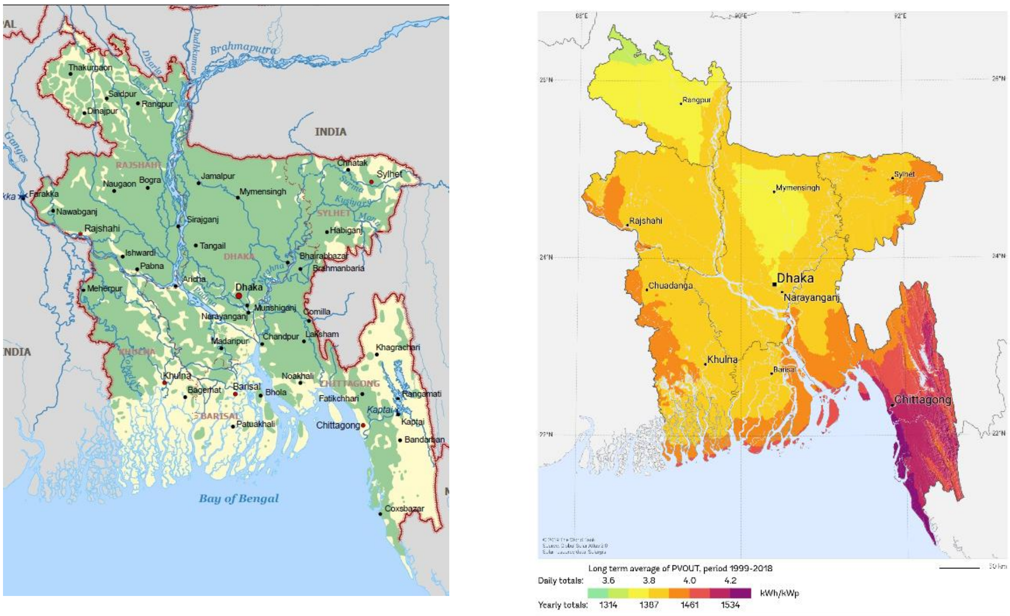


(2.1.b)

Figure 2. 1 Scenarios and trends of Bangladesh agriculture and its related energy statistics.
Sources: Author's preparation using data retrieved from https://www.fao.org/faostat, http://www.bpc.gov.bd/, and SREDA (2022).
Note: This figure presents the trends in agriculture, solar installation for irrigation, and petroleum products used in various sectors in Bangladesh. The first image (2.1.a) depicts agricultural value production and various agriculture-related emissions statistics in Bangladesh for the period 1990-2020. Panel 2.1.b shows petroleum products' sales in different sectors for the period 2017-2021 and annual solar irrigation capacity changes for the period 2012-2022. Various periods lable for different variables. Units of measurements of the variables are in parentheses in the vertical axes titles.

In addition to being an agrarian country, Bangladesh's cropping method is highly resource intensive and hence costly. More than 40% of the total cultivation costs go to irrigation (SREDA, 2022). Figure 2.2.a shows the irrigation intensity for the selected variables in the country. The irrigated area share in total cultivated land for crops is 65.50% and 58.60% of irrigation uses groundwater sources (BBS, 2022). Groundwater-based irrigation requires intensive energy and high-powered pumps. According to the Bangladesh Petroleum Corporation (BPC) estimates, agriculture consumed 15.49% of petroleum products in 2019-20 (BPC, 2022) and the rate of sales has been steady for almost a decade (Figure 2.1.b). This indicates an increased dependence on diesel irrigation, because irrigation mostly uses such products. Both surface water and groundwater irrigation modes use diesel on 3.4 million hectares of land (SREDA, 2022). More than 80% of pumps are diesel-operated while the electricity grid is not reachable to 40% rural population (Islam et al., 2017). More importantly, solar installation for irrigation has drastically reduced since 2019 (Figure 2.1.b). These statistics suggest that resource-use inefficiency is alarming in irrigation in the country. Uncertainties in farmers' cropping preferences and underutilization of solar plants may have caused such a lag in the implementation of projects (Mitra et al., 2021). In such a case, the existing energy transition roadmap and renewable technology adoption process may jeopardize Paris Agreement commitments for the country. The pledge is to reduce 15.12% of GHGs by 2030 to support global climate actions and agriculture will support this matter 0.65% conditionally (i.e., subject to external technology and financial support) and 2.3% unconditionally (GOB, 2021). In this regard, the country is making progress in solar energy projects. Bangladesh's renewable energy consumption amounts to 28% of the total energy consumption and solar contributes the most (58% of the total renewable energy consumption) (IRENA, 2022). However, only 3.57% of electricity generation comes from renewable energy and solar home systems use most of it (SREDA, 2022). Since the country has energy supply shortfalls and frequent disruptions, solar irrigation is an efficient technology choice. In fact, sunshine across the country is ample. Most areas are generating solar power 3-4 kWp daily (Figure 2.2.b). At the policy level, solar transition action has effectively taken into account the NDC planning, particularly for irrigation. In this regard, the government introduced an instrument to identify potential locations for solar installation, namely *SIP (Solar Irrigation Project) site prioritization tool* (SREDA, 2019). This tool scores the locations as suitable areas for solar projects based on the severity of water and energy stress and cropping intensity.



(2.2.a) (2.2.b)

Figure 2. 2 Maps of irrigation intensity and solar radiation in Bangladesh.

Source: Retrieved from https://storage.googleapis.com/fao-aquastat.appspot.com/countries_regions/pdf/BGD-map_detailed.pdf, and https://solargis.com/maps-and-gis-data/download/bangladesh.
Note: The green areas in 2.2.a shows the irrigation network across the country. Image 2.2.b shows the area-wise potential of the average daily and yearly electricity generation capacity from a 1KW solar PV system for the period of 1999-2018.

Solar irrigation in Bangladesh is a large-scale project that is highly subsidized and sponsored by both the government and private organizations. However, pump installation costs reduced by more than 60% since 2012 (IDCOL, 2022). Currently, there are 2925 solar systems with a total capacity of 54.455MWp in 52[2] (out of 64) major administrative areas or districts. The major sponsors are IDCOL, BMDA, BADC, and BREB[3]. Irrigation itself minimizes yield risk (Salazar et al., 2019), thus the adoption of solar irrigation can ensure both input-use efficiency and output maximization.

2.2.2 Mechanism and operation models of a solar irrigation system

The basic mechanism of a solar irrigation system has a set of technologies that convert solar energy into electricity to channel water from a source to plants. Such a system requires a water source, solar panels, a water pump motor, a pump inverter, a metering device, and water tanks. The following Figure 2.3 describes the solar irrigation process and its technical parts in real-time in Bangladesh. A solar system can replace a minimum of eight (08) pumps and thus 32 tons of CO_2 emissions can be reduced (IDCOL, 2022). Solar irrigation has both financial viability and environmental sustainability. However, this is not a mature technology and there are some inherent challenges in solar irrigation models (Mitra et al., 2021). These factors may have been responsible for the slacking adoption and dissemination of this technology. There are two types of *business models* operating in solar irrigation projects (Table 2.1). In both models, equipment, and installations are sponsored and subsidized and farmers rarely pay for the upfront costs. The significant differences between the two models are in system capacity, system ownership, and operation roles. In the ownership model, the operation requires a higher level of coordination and integrity, and the fee-for-service model is flexible in terms of operation and alternative uses of a plant. Because of such

[2] During the data collection period 2021-2022, there were 2696 systems in 28 districts.

[3] IDCOL is Infrastructure Development Company Limited, established by the government of Bangladesh. BMDA (*Barind* Multipurpose Development Authority), BADC (Bangladesh Agricultural Development Corporation) and BREB (Bangladesh Rural Electrification Board) are all government organizations related to agriculture and power distribution. The installed capacities by IDCOL, BMDA, BADC, and BREB are respectively 42.08MWp, 4.37MWp, 2.43MWp and 1.2MWp (SREDA, 2022). IDCOL installed 1515 pumps (out of 2818) to serve 65000 farmers covering 21112 hectares of land (IDCOL, 2022).

flexibility, the fee-for-service model could reach a large number of farmers, though providers found it less viable (e.g., a low revenue collection in terms of an agreed irrigation charge) (Mitra et al., 2021; IDCOL, 2022). However, none of the models uses a coherent method or any eligibility criteria to select potential farmer users.

Water source

•This solar system uses surface water reservoir. This area has an acute groundwater stress, which is one of the criteria for solar irrigation area selection.

Solar panels

•There can be one large panel or multiple small panels in a system. This system uses 72 panels.

Pump

•This image shows pump mechanism for water reception. This pump's capacity is 14.75kW and pump head is 40 meters.

Metering

•This pre-paid metering system monitors irrigation water withdraw and farmers pay accordingly.

Tank

•This water tank channelizes water to fields. Multiple tanks are used in large coverage areas. Some tanks store water for drinking purpose only.

Irrigation

•Fields receive water from tanks through a pipeline. This system provides 50 farmers with necessary irrigation water.

Figure 2. 3 Mechanism of a solar irrigation system in Bangladesh.

Source: Author's preparation from field observation and discussion.
Note: This figure presents the technical features and mechanism of a solar irrigation system in Bangladesh. The photos are taken during field visits to a surface water-based solar system in Nachol, Chapai Nawabganj, one of the study districts. A pump's head represents the water lifting strength from a low to a high point. That is why in dug well modes pumps require a longer head and a higher capacity to lift water from the ground. The technical features and operations are similar in both irrigation modes.

Table 2. 1 Features of solar irrigation models in Bangladesh.

Criteria	Fee for service model	Ownership model
Target	Small and medium farmers	Small and marginalized farmers
Financier	IDCOL	BMDA, BADC, BREB, RDA
Financing	Sponsorship (100%)	Grant-based (100% or less)
Capacity	High capacity, 28 kW	Low capacity, 5 kW
Connection	Off-grid	Grid-connection and off-grid
Requirement	No electricity grid nearby, the financial viability of systems	Surface water availability, groundwater depth, irrigation requirement and solar condition
Purpose	Agribusiness and irrigation	Irrigation and drinking water
Ownership	Private sponsors	Farmers, individual or group
Operation	Sponsors	Farmers
Roles	Sponsors provide and own equipment and farmers pay sponsors for water	Financiers provide equipment, farmers may or may not pay for equipment, farmers may sell water to others
Challenges (to scale up)	**Economic returns, revenue collection, infrastructure for alternative use, following institutional guidelines, farmers' selection**	**Implementation through farmers' training, user rights, irrigation management, and control**

Source: Author's preparation using Mitra et al. (2021), SREDA (2019) and IDCOL (2022).
Note: This comparison table presents two types of solar irrigation models for various criteria in Bangladesh. The upscaling challenges in the last row are in bold letters to emphasize the motivations of this study.

2.3 Study area and sample selection process

2.3.1 Selection of the study area

This research follows a multi-stage clustered random sampling procedure to select the study area and the study participants (Table 2.3). The study area includes 12 major administrative regions (i.e., districts) in Bangladesh[4]. The country has almost equal solar exposure in all districts. Due to technical viability, providers' district selection for solar irrigation projects may be random. However, plant location depends on surface water availability and electricity demand. To address this probable location bias, I select the districts based on solar network heterogeneity. In this process, I first

[4] This survey uses the agricultural production data from July 2020 to June 2021. During the time of this survey (2021-2022 period), only 28 districts had solar irrigation coverage. The average capacity of all systems was 1.82 MW and the average number of systems for all districts was 96. High solar adopted areas include districts with solar systems with capacity and numbers above the average values and low adopted areas include the same with values below the average. In this regard, 13 districts have high adoption and 15 districts have low adoption. Solar plants running for at least two years are selected in 12 districts that cover 40% of the total area under solar irrigation networks in the country.

sort groups by the total number and capacity of solar systems. Then I randomly select 6 (out of 13) districts with high adoption networks and 6 (out of 15) districts that have low adoption networks (Figure 2.4). This also allows me to elucidate spatial heterogeneity of adoption behaviour. This is the first-stage cluster sampling. There may be plant-size variations within a cluster and thus I draw an equal number of farmers from each district. In each district, I randomly select one sub-district. Irrigation requirements do not vary within districts. There is not much variation in average plant capacity at this level. Finally, in each subdistrict, I purposively select one village (i.e., the smallest geographical unit) based on solar user group size. In a village, an average size[5] solar plant can serve 30-50 farmers. If the user group size is less than 40 (e.g., in low network areas), I select another nearby village so that there is no locational difference at the sub-district level. I select finally 14 villages and this is the second cluster sampling that includes both solar and non-solar user farmers.

The following Table 2.2 presents some of the agriculture and irrigation profiles of the study area. Among the 12 districts, the amount of cultivated land is the largest in *Dinajpur* and the smallest in *Dhaka*. In 2021 estimates, the average cultivated land amount is 186690.92 (0.18 million) hectares and the average number of irrigation modes amounts to 60268 in the study area. The average numbers of DTW, STW, and LLP are respectively 1342, 56790, and 2129. The maximum number of irrigation modes, inclusive of DTW, STW, and LLP are available in *Dinajpur* and a minimum of the same are available in *Barisal* (Figure 2.5). The average solar system capacity in is 2.15MWp. *Naogaon* has the largest number of solar systems (448), while the total capacity of systems is the highest in *Dinajpur* (10.635MWp). Both *Dhaka* (5, 0.028MWp) and *Magura* (3.041MWp) have a small number of systems with a lower

[5] The average capacity of a plant in the study area is 13KWp.

total capacity. The main crops grown in the study area include paddy, wheat, jute, maize, lentils, sugarcane, and potato.

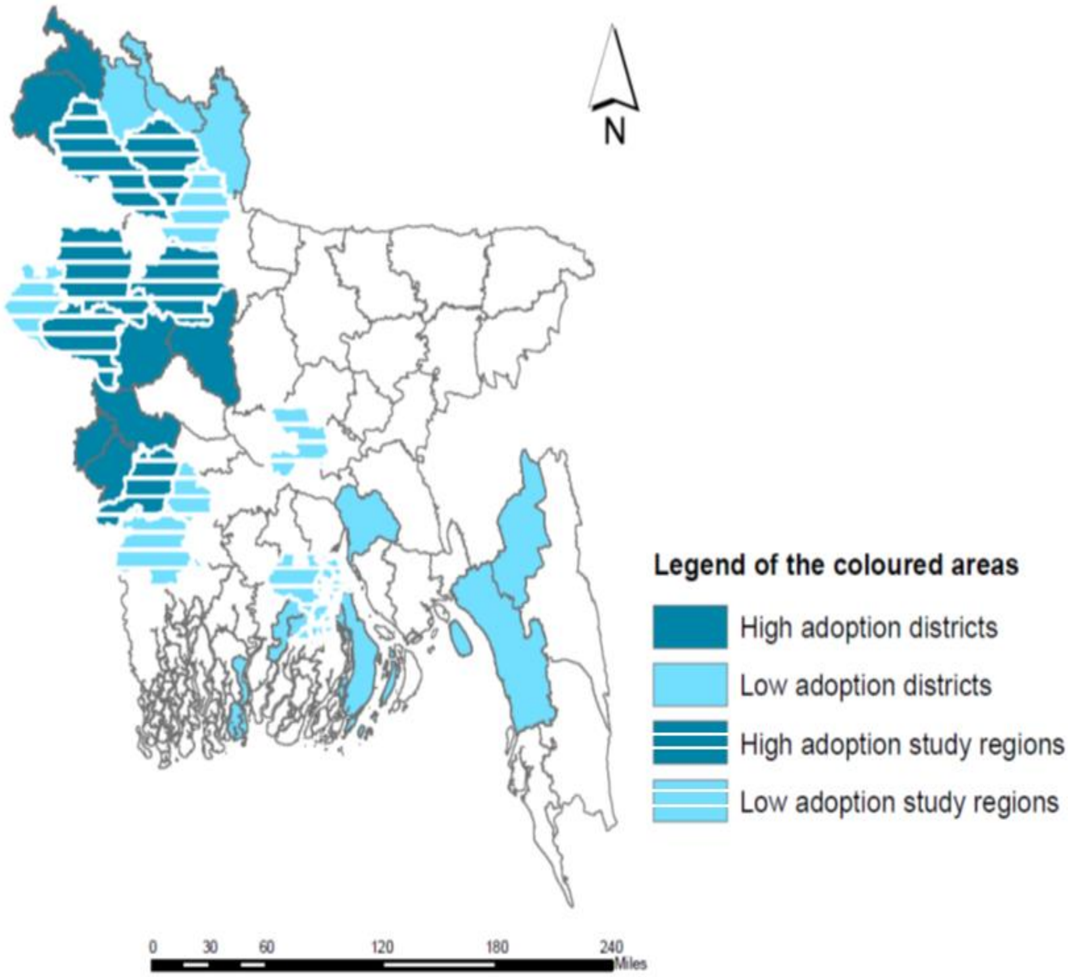


Figure 2. 4 Map of solar network districts and study area in Bangladesh.

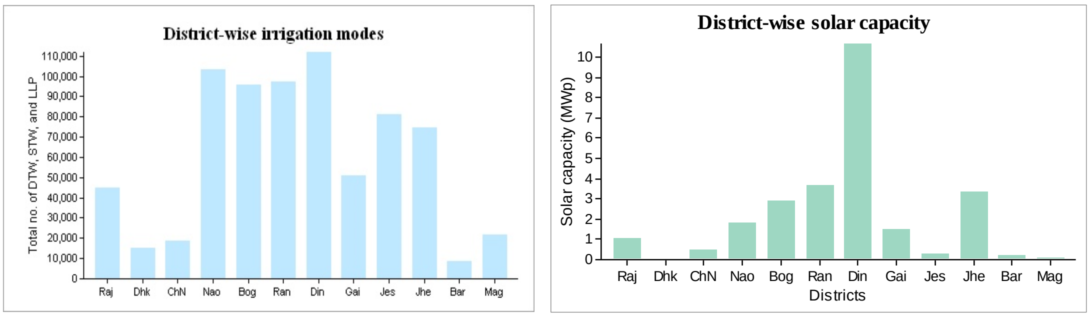
Source: Author's preparation.

This figure presents the map of the study country and 12 study regions including high and low solar-adopted districts in Bangladesh. It appears on the map that high (solar) adopted districts are concentrated and mostly located in the north-western parts of the country.

Table 2. 2 Agriculture and irrigation profile of the study area.

Study area and sample size		Agricultural land	Irrigation water-lifting modes			Solar systems	
Districts	Sample	Total cultivated land (Ha) 2021	DTW (No.) 2021	STW (No.) 2021	LLP (No.) 2021	Solar systems (No.) 2022	Total capacity (MWp) 2022
Rajshahi	76	158172	2761	34272	7695	94	1.032
Dhaka	52	82442	121	12863	2313	5	0.028
Chapai Nawabganj	66	129751	1680	14415	2325	90	0.455
Naogaon	66	284262	3770	95891	3764	448	1.822
Bogra	66	224840	2817	92529	360	116	2.911
Rangpur	66	201491	1021	96375	47	308	3.677
Dinajpur	70	288432	2341	109028	495	418	10.635
Gaibandha	66	160229	668	49923	102	65	1.451
Jessore	70	198416	564	80295	76	19	0.242
Jhenaidah	70	146918	354	74445	1	100	3.358
Barisal	66	174738	0	0	8355	13	0.161
Magura	66	190600	6	21523	15	3	0.041
Study area average	---	186690.92	1342	56797	2129	140	2.15

Source: *Yearbook of Agricultural Statistics*, various issues, SREDA (2022) and retrieved from http://www.bangladesh.gov.bd/site/view/district-list/.
Note: This table reports the selected agriculture and irrigation statistics of the study area in Bangladesh. Bangladesh has 64 major administrative areas, i.e., districts. In the country, there are three major irrigation water-lifting modes, namely deep tubewell (DTW), shallow tubewell (STW), and low lift pumps (LLP). DTW and STW use groundwater while the other device uses surface water. Diesel irrigation is highly concentrated in STW and LLP modes. However, solar systems mostly use dug wells and LLP. Figure 2.5 presents the visualization of the data reported in this table.



(2.5.a) (2.5.b)

Figure 2. 5 District-wise irrigation modes and solar capacity.
Sources: Author's preparation.
Note: This figure visualizes irrigation modes and solar capacity of the study area reported in Table 2.2. The blue bars in Graph 2.5.a shows different levels of irrigation modes at the district level. Finally, Graph 2.5.b presents the variation in the total capacity of solar irrigation systems at the district level. Units of measurements of the variables are in parentheses in the vertical axes titles.

Table 2. 3 Sampling frame and randomization process.

Sorting 28 districts that have solar irrigation systems based on the number of solar systems	
Two clusters by solar network intensity (at country level)	
13 high adoption districts	15 low adoption districts
Randomly selecting 6 districts from each cluster	
6 high adoption districts	6 low adoption districts
Randomly selecting 12 subdistricts and then one village in each subdistrict	
Collecting separate lists of farmers using solar and non-solar irrigation in each village	
Two clusters by irrigation energy use (at village level)	
Randomly selecting 66 farmers in each village	
33 solar user-farmers (minimum 26 and maximum 35)	33 non-solar user-farmers (minimum 26 and maximum 35)
Random selection of **800 farm-households** in 14 villages	
400 solar user-farmers	**400 non-solar user-farmers**

Source: Author's preparation.
Note: This table presents the multistage cluster randomization process to select the study area and the study sample of farm-households.

2.3.2 Selection of sample farmers

This study recruits a sample of 800 farmers for the choice experiments and a face-to-face survey. The sampling frame includes two separate groups of farmers (400 solar and 400 non-solar users) and randomization is performed at the user (i.e., farmer) level to select the sample. Randomization at the user level instead of the group level avoids sample contamination by removing treatment spill-over effects (Duflo et al., 2009). Therefore, to begin the sampling process, surveyors collected two separate lists of solar irrigation users and non-solar irrigation users at the village level. The non-solar group includes farmers using diesel and electricity-operated pumps. Then 33 solar users and 33 non-solar users are randomly selected for two groups. In this regard, since solar irrigation use is a given intervention, the strategy for sample balance uses one inclusion criterion that providers use for site selection, i.e., land size. The farmers' lists contain information on the amount of land size of farmers. Based on these lists and confirmed by field survey, there is no significant difference between solar irrigation adopters and non-adopters (the *p*-value of difference is 0.326 in Table 2.4.4). Thus, the average land size is the matching or selection criterion for a control group sample of 33 non-solar users[6]. In each study region, thus a sample of 66 farmers in two groups are randomly selected. Both groups in a study region live in the same village. This confirms that geographical conditions and cropping patterns are similar for both groups of farmers and consequently justifies the sample selection randomness. Farmers' self-selection for solar irrigation may or may not be random because plant location decision depends on several structural conditions as well as the decision-making of potential users. Non-randomization may happen at this point because land size is a sufficient condition here. A provider announces a circular for solar users' enlistment and thus it can reduce the selection bias. Potential adopters may not consider only their lands' proximity to a plant but also become interested in energy sources because of various economic and non-economic factors. There are sometimes multiple options for a suitable location of plant installation in a village. Out of those options, the provider finalizes a location after confirming the land size, preference of a land-owner and agreeing on a group of

[6] In one village out of 12 districts, it was not possible to select 33 solar farmers due to the small size of solar plants and the small number of users. In that village, 25 farmers for each group are selected. To get a balanced sample at the district level, in four districts, 35 farmers are selected for each group (Table 2.2).

potential solar adopters. A provider installs a plant on an individual farmer's land and that farmer becomes the system operator for a group of solar adopters.

2.4 Farm-level characteristics

This study conducted a primary survey of farming households with a structured questionnaire. Respondents for this field survey are farmers, who generally are the household heads and keep all the household and farming-related records. Calculation and analysis of farm-level characteristics use coded and cleaned data. The following sections describe the general characteristics of the full sample of 800 farming households, and comparisons of the two groups of farmers, i.e., solar and non-solar farmers.

Socio-demographic characteristics

The average age of farmers is 46 years with a below primary level education (4.72 years of schooling (Table 2.4.1). Approximately 22% of farmers are involved in a non-farm activity. Farmers earn annually an average of BDT14000 and total family income is slightly higher than this amount (BDT18000 approximately). Farming families have on average 4 members in the house. In the case of group comparisons, solar users have a higher level of education and income diversification than non-solar users. Non-solar farmers have a longer farming experience than solar users.

Livelihood activities

Six types are observed in the study area in cases of main and secondary livelihood activities (Table 2.4.2). Agriculture is the primary and major (97.13%) livelihood activity and business is the major secondary (13.25%) livelihood for the whole sample and both solar and non-solar groups. Other livelihoods in both primary and secondary categories are service, rickshaw/van-driving or -pulling, and day labouring. The lowest numbers of respondents are teachers. It is possible that the head of the family (who is the respondent) is not a farmer. In that case, another member(s) of that family is responsible for cultivation; hence, the sample includes the household.

Table 2.4. 1 Farmers' socio-demographic characteristics.

Socio-demographic characteristics	Full sample	Solar	Non-solar	*p*-value of difference
	Mean (Std. dev.)/ percentage	Mean (Std. dev.)/ percentage	Mean (Std. dev.)/ percentage	
Age (years)	45.41 (13.168)	44.90 (13.514)	45.93 (12.809)	0.266
Education (years)	4.72 (5.172)	5.15 (5.285)	4.29 (5.027)	0.018
Income diversification (% yes)	21.75	24.50	19.00	0.059
Annual income (BDT)	13844.88 (6783.04)	13530.63 (6378.37)	14159.13 (7159.118)	0.190
Farming experience (years)	26.15 (13.272)	25.14 (13.293)	27.17 (13.191)	0.031
Household size	4.023 (1.099)	3.98 (1.106)	4.067 (1.093)	0.261
Total family income	18025.13 (11822.44)	17789.39 (11976.15)	18260.88 (11676.94)	0.573

Source: Author's calculation from field survey.
Note: This table reports farmer's demographic characteristics and household's socio-economic status. Income diversification indicates farmer's involvement in any non-farm activity. Means and standard deviations (in parentheses) are reported for numeric/scale variables and binary variables are reported in percentage frequency of the 'yes' response. Units of variable measurement are in parentheses in the first column. A significant *p*-value (i.e., less than at least 0.10) indicates that solar and non-solar using farmers differ in that category.

Standard of living

Indicators of house conditions presented in Table 2.4.3 reflect farm-households' standard of living. Almost all farmers own their houses and have electricity access in their houses. More than 75% of the farmers inherited houses from their ancestors. The average number of rooms is three and the average number of assets is nine in the house. Most houses are made of brick or cement (57%). Farmers also have tin/timber (26.5%) and mud (16.38%) houses. Approximately, 89% of farmers use sanitary toilets. The average period of electricity access is 12 years. In all categories except for inheritance status, if the house is made of brick/cement and a *kancha* type of toilet, non-solar users have higher frequencies than solar users. However, group differences are not significant.

Table 2.4. 2 Farmers' livelihood activities.

Livelihood activities (% yes)	Full sample		Solar		Non-solar		*p*-value of difference	
	Primary	Secondary	Primary	Secondary	Primary	Secondary	Primary	Secondary
Agriculture	97.13	2.75	97.25	2.75	97.00	2.75	0.833	1.00
Business	1.50	13.25	1.25	14.25	1.75	12.25	0.561	0.405
Service	0.63	2.63	1.25	4.50	-	0.75	-	0.000
Teaching	-	0.38	-	0.25	-	0.50	-	0.563
Rickshaw/ van	0.25	1.50	-	1.00	0.50	2.00	-	0.245
Day laboring	0.50	1.25	0.25	1.75	0.75	0.75	0.316	0.204

Source: Author's calculation from field survey.
Note: This table reports the main/primary and secondary occupations of farmers. In the study area for the full sample of 800 farmers, 78.25% of them do not have any secondary occupation. For solar and non-solar the frequencies are 75.50% and 81.00% respectively. Each category is reported in the percentage frequency of a 'yes' response. A significant *p*-value (i.e., less than at least 0.10) indicates that solar and non-solar using farmers differ in that category.

Table 2.4. 3 Farm-household's standard of living.

Standard of living	Full sample Mean (Std. dev.)/ percentage	Solar Mean (Std. dev.)/ percentage	Non-solar Mean (Std. dev.)/ percentage	*p*-value of difference
Own house (% yes)	98.63	98.25	99.00	0.363
Inherit house (% yes)	75.25	77.25	73.25	0.190
Rooms (number)	2.93 (1.387)	2.86 (1.421)	3 (1.351)	0.154
House materials (% yes for 4 categories)	57 (Brick/cement)	57.75 (Brick/cement)	56.25 (Brick/cement)	0.669
	26.5 (Tin/timber)	25.75 (Tin/timber)	27.25 (Tin/timber)	0.631
	16.38 (Mud/mud-brick)	16.50 (Mud/mud-brick)	16.25 (Mud/mud-brick)	0.924
	0.13 (Hay/bamboo)	-	0.25 (Hay/bamboo)	-
Toilet type (% yes for 3 categories)	89.38 (Sanitary/slab)	88.00 (Sanitary/slab)	90.75 (Sanitary/slab)	0.207
	10.38 (*Kancha*)	12.00 (*Kancha*)	8.75 (*Kancha*)	0.132
	0.25 (Open space)	-	0.50 (Open space)	-
Access to electricity (% yes)	99.75	99.50	100.00	0.157
Electricity period (years)	12.01 (10.144)	11.40 (9.942)	12.62 (10.318)	0.082
Assets (number)	9.18 (3.957)	9.06 (3.851)	9.30 (4.062)	0.387

Source: Author's calculation from field survey.
Note: This table reports farmers' standard of living determined by house ownership status, house size and house materials, sanitation standard, electricity access, and asset possession. Assets include mobile, television, refrigerator, computer, internet access, furniture, electronic appliance, and farm machinery. Brick/cement and tin/timber-built houses resemble a higher standard of accommodation in the study area. Means and standard deviations (in parentheses) are reported for numeric/scale variables and binary variables are reported in percentage frequency of the 'yes' response. Units of variable measurement are in parentheses in the first column. A significant *p*-value (i.e., less than at least 0.10) indicates that solar and non-solar using farmers differ in that category.

Farm and farming characteristics

Farmers have on average of 15.14 decimals of homestead land and 107 decimals of cultivable land. Most of the cultivable lands have low elevations (71.25%) and the soil is clay-type (56.13%). Farmers also have large amounts of medium (26.63%) and high (36.25%) lands. Other soil types in terms of importance are loamy (32.50%), sandy-loamy (14.13% and clay-loamy (12.63%). Both land elevation and soil types may vary for an individual farmer. However, elevations and soil types are mostly homogenous at the district level. Solar users have a lower amount of cultivable and homestead land than non-solar users. In all land and soil types except for the sandy-loamy one, the frequencies are above the average for solar users. Major irrigated crops include paddy (96.75%), vegetables (21.75%), jute (6.50%), wheat (4.38%), and maize (3.63%). Almost all farmers grow food crops (98.25%). Mono (75.38%) cropping is the cultivation pattern of most farmers. Farmers also follow inter (21.25%) and multi (23.50%) cropping patterns. The two groups of farmers are similar in cropping patterns. In farming operation cases, the annual average amount of irrigated land for all crops amount is 80.34 decimals. For all crops, farmers on average use irrigation approximately for 28 days in a year and per irrigation they use 2 hours. The average irrigation cost annually for all crops is 4032.46 BDT. Farmers get on average 2184.66 kg of crops and their average land productivity is 31.08 kg per decimal annually. Overall, irrigation cost, irrigation frequency, and irrigation timing are lower for solar users than for non-solar users. Solar users spend 2374.15 BDT less than non-solar farmers. Similarly, solar users require 4 irrigations and spend 1.8 hours less than non-solar users do. Although non-solar users get on average a higher yield in a year, land productivity is higher for solar users.

Table 2.4. 4 Farm and farming characteristics.

Variables	Full sample Mean (Std. dev.)/ percentage	Solar Mean (Std. dev.)/ percentage	Non-solar Mean (Std. dev.)/ percentage	*p*-value of difference
Land possession (decimal)				
Total cultivated land	107.01 (95.489)	103.69 (88.171)	110.32 (102.29)	0.326
Homestead land	15.14 (13.328)	13.83 (11.127)	16.45 (15.115)	0.005
Total	122.15 (98.458)	117.52 (90.223)	126.78 (105.968)	0.184
Land elevation (% yes)				
Low land	71.25	74.75	67.75	0.028
Medium land	26.63	27.00	26.25	0.811
High land	36.25	39.75	32.75	0.040
Soil type (% yes)				
Clay	56.13	60.25	52.00	0.019
Clay-loamy	12.63	17.00	8.25	0.000
Loamy	32.50	33.50	31.50	0.546
Sandy	5.50	6.25	4.75	0.353
Sandy-loamy	14.13	11.00	17.25	0.011
Major irrigated crops (% yes)				
Paddy	96.75	96.50	97.00	0.691
Wheat	4.38	4.50	4.25	0.863
Jute	6.50	5.25	7.75	0.152
Vegetables	21.75	22.75	20.75	0.494
Maize	3.63	4.25	3.00	0.345
Crop type (% yes)				
Food crop	98.25	99.00	97.50	0.106
Cash crop	1.75	1.00	2.50	0.106
Cropping pattern (% yes)				
Mono	75.38	75.25	75.50	0.935
Mixed	-	-	-	-
Inter	21.25	21.00	21.50	0.863
Multi	23.50	23.50	23.50	1.000
Crop input-output profile				
Annual average of irrigated land (decimal)	80.34 (75.712)	66.87 (63.253)	93.82 (84.344)	0.000
Annual average of irrigation frequency (number of days)	27.39 (27.406)	25.28 (23.855)	29.51 (30.432)	0.029
Annual average irrigation timing (an hour per irrigation)	2.08 (2.969)	1.17 (2.061)	2.98 (3.429)	0.000
Annual average irrigation cost (BDT)	4032.46 (4033.492)	2845.38 (2394.096)	5219.54 (4901.206)	0.000
Annual average yield (kg)	2184.66 (2572.674)	1747.14 (1604.036)	2622.18 (3208.917)	0.000
Annual average land productivity (kg/decimal)	31.08 (42.137)	33.14 (55.264)	29.03 (22.205)	0.167

Source: Author's calculation from field survey.

Note: This table reports farm and cropping-related features. All land amounts are in decimals. 1 decimal is equivalent to 0.004 hectares in Bangladesh. Cultivated land size is the group-matching criterion. Solar and non-solar farming households are similar in cultivated land-size distributions (*p*-value of difference in t-test, 0.3262). However, their homestead land distributions differ (*p*-value of difference in t-test, 0.0054). Cropping patterns and crop types are similar for solar and non-solar groups. Inter-cropping means different crops cultivated in a season on the same land and multi-cropping implies different crops in different seasons. Farmers' groups differ significantly in input-output profile. Means and standard deviations (in parentheses) are reported for numeric/scale variables and binary variables are reported in percentage frequency of the 'yes' response/category. Units of variable measurement are in parentheses in the first column. A significant *p*-value (i.e., less than at least 0.10) indicates that solar and non-solar using farmers differ in that category.

Perception of soil fertility condition and sustainable agriculture

Farmers have three types of perception of soil fertility condition, i.e., increasing, decreasing, and no change (Table 2.4.5). Most farmers perceive that the soil fertility of their land is increasing (75.75%). Solar users have a higher frequency than non-solar users. Only 16% of the farmers perceived decreasing soil fertility and non-solar users have a higher perception in this case. As for the reasons for increasing soil fertility, farmers mostly give credit to the use of low-carbon inputs (67.00%) (e.g., green manure, organic fertilizer, and so on). The other two influential factors include the use of renewable irrigation (43.07%) and crop change (28.05%). Perceptions of the two groups vary to some extent across the contributing factors. A very small number of non-solar farmers mention the positive impact of renewable irrigation (4.83%) on soil fertility. These non-solar users may have used renewable irrigation in the past or use grid electricity currently. The most crucial factor responsible for decreasing soil fertility is chemical input overdose (71.09%). The other two important factors include similar cropping patterns (41.84%) and mono-cropping (50.78%). The notable point in this regard is that diesel irrigation (7.81%) and machinery use (3.13%) are the least concerned factors of soil fertility reduction for both groups. Among the farmers, the mostly used sustainable agricultural practice is the application of organic fertilizer (79.88%). Farmers also use traditional or indigenous methods (49.00%). Only 5.63% of the farmers practice no or limited tillage. Efficient irrigation is the least followed sustainable method (3.88%). Overall, solar users are less perceptive of their sustainable practices than the non-solar ones. However, 4.13% of the farmers do not use any of the sustainable methods and only 0.50% of the solar farmers fall into this category.

Table 2.4. 5 Farmers' perception of sustainable agricultural technologies.

Variables (% yes)		Full sample	Solar	Non-solar	*p*-value of difference
Perception of soil fertility condition	Increasing	75.75	79.00	72.50	0.032
	Decreasing	16.00	14.25	17.75	0.177
	No change	8.25	6.75	9.75	0.123
Reasons for an increasing soil fertility condition	Low-carbon input	67.00	62.66	71.72	0.017
	Crop change	28.05	31.96	23.79	0.025
	Renewable irrigation	43.07	78.16	4.83	0.000
	Efficient tillage	4.61	5.38	3.78	0.348
Perception of decreasing soil fertility condition	Similar crops	41.84	51.52	31.96	0.005
	Mono cropping	50.78	43.86	56.34	0.163
	Machinery use	3.13	1.75	4.23	0.428
	Diesel irrigation	7.81	3.51	11.27	0.105
	Chemical overdose	71.09	71.93	70.42	0.853
	Groundwater	9.38	7.02	11.27	0.416
Sustainable practices	Efficient irrigation	3.88	3.00	4.75	0.200
	Organic fertilizer	79.88	76.25	83.50	0.011
	Traditional/indigenous method	49.00	41.75	56.25	0.000
	No/limited tillage	5.63	4.50	6.75	0.168
No sustainable practice		4.13	0.50	7.75	0.000

Source: Author's calculation from field survey.

Note: This table reports farmers' perceptions about soil fertility change over time and sustainable agricultural technologies. Farmers perceive soil fertility changes by observation and through farming experience. The perception of sustainable technology is the farmer's knowledge about the technology he/she uses. Categories of increasing and decreasing soil fertility reasons are calculated for the sample of farmers having the respective perceptions. The sample size for an increasing perception is 606, for a decreasing perception the same is 128, and 66 farmers are in the no-change category. All categorical variables are reported in percentage frequency of a 'yes' response. A significant *p*-value (i.e., less than at least 0.10) indicates that solar and non-solar using farmers differ in that category.

Table 2.4. 6 Farmers' institutional accessibility.

Variables (% yes)	Full sample	Solar	Non-solar	*p*-value of difference
Institutional accessibility	65.00	67.00	63.00	0.236
Used information from the sources				
Agriculture extension office	37.63	40.75	34.50	0.068
Neighboring farmers	47.63	48.75	46.50	0.524
Relatives	7.50	7.50	7.50	1.000
Research institutions	1.25	2.00	0.50	0.056
NGOs	7.25	6.75	7.75	0.586
Mass media	8.88	8.75	9.00	0.901
Local trader	29.25	30.75	27.75	0.351
Any training received	18.50	22.00	15.00	0.011
If knows the solar irrigation starting time	85.38	98.25	72.50	0.000
Bank account	26.25	30.75	21.75	0.003
Access to agricultural credit	14.89	15.25	14.54	0.766
Access to subsidy	5.88	5.75	6.00	0.881
Access to the village market	34.50	33.75	35.25	0.655
Access to the local market	77.50	79.00	76.00	0.310
Access to the urban market	43.13	46.75	39.50	0.038

Source: Author's calculation from field survey.

Note: This table reports farmers' access to various institutional sources and their assistance. All binary and categorical variables are reported in percentage frequency of the 'yes' response. Local trader category for cultivation-related information includes fertilizer retailers, pesticide companies, and solar equipment providers. The percentages for solar farmers in the cases of agricultural extension and local traders are above the average values and non-solar farmers possibly due to their access to solar providers, either the government or private sponsors. A significant *p*-value (i.e., less than at least 0.10) indicates that solar and non-solar using farmers differ in that category.

Institutional accessibility

In the full sample, 65% of the farmers have access to institutional information about crop production, inputs, energy, and other technologies, and only 18.50% of farmers receive any relevant training (Table 2.4.6). Solar users have larger access to information and training than non-solar users. Farmers mostly use the information received from agricultural extension (37.63%), neighboring farmers (47.63%), and local input traders (29.25%). Solar users receive information more from these sources than non-solar users do. More than 85% of farmers are aware of the starting time of solar irrigation in their locality. Small fractions of farmers have a bank account (26.25%), agricultural credit (14.89%), and subsidy (5.88%). In the case of market access, farmers mostly purchase inputs and sell crops in the local market (77.50%). They also have significant access to urban markets (43.13%). Solar users have larger access to local and urban markets than non-solar users.

Irrigation-energy profile

In the study area, all farmers use power pumps for irrigation. In the case of equipment ownership, individual ownership is high (approximately 50%) (Table 2.4.7). The reason is that most farmers who use diesel pumps are owned by individual farmers. Governments own 20.81%, NGOs own 28.88% and the community owns 0.38% of the equipment. Ownership type varies considerably between the groups. Government and NGOs own solar pumps, while individual farmers own more than 90% of the non-solar pumps. The average age of these individually purchased pumps is 12.70 years. Farmers bought them at 12135.53BDT and they spend on average 2721.13BDT for yearly maintenance.

Table 2.4. 7 Farming irrigation-energy profile.

Variables	Full sample Mean (Std. dev.)/ percentage (yes & category)	Solar Mean (Std. dev.)/ percentage (yes & category)	Non-solar Mean (Std. dev.)/ percentage (yes & category)	*p*-value of difference
Equipment ownership (% yes for 4 categories)	49.94 (individual) 0.38 (community) 20.81(Government) 28.88 (NGOs)	9.75 (individual) - 33.00(Government) 57.25 (NGOs)	90.84 (individual) 0.76 (community) 8.40(Government) -	0.000 - 0.000 -
Pump purchased length (years)	12.70 (7.651)	-	-	-
Pump purchase cost (BDT)	12135.53 (5169.938)	-	-	-
Maintenance cost (BDT)	2721.13 (1575.439)	-	-	-
Pump capacity (KW)	10.07 (5.288)	12.88 (3.651)	7.27 (5.189)	0.000
Pump head length (meter)	36.72 (23.792)	46.67 (25.195)	26.78 (17.336)	0.000
Land-pump distance (meter)	193.38 (315.909)	191.57 (282.234)	195.20 (346.675)	0.871
Land—water source distance (meter)	1566.77 (3197.215)	2298.64 (3827.138)	834.90 (2179.235)	0.000
If used a different energy source in the past (% yes)	65.50	98.75	32.25	0.000
Past energy source	1.91 (solar) 89.50 (diesel) 8.59 (electricity)	- 88.61 (diesel) 11.39 (electricity)	7.75 (solar) 92.25 (diesel) -	- 0.242 -
Solar use period (years)	-	4.43 (1.906)	-	-
Water source (% yes for 2 categories)	80.63 (ground) 18.63 (surface) 0.75 (both)	78.50 (ground) 21.50 (surface) -	82.75 (ground) 15.75 (surface) 1.50 (both)	0.128 0.037 -
If excess fertilizer needed due to irrigation	6.63	3.75	9.50	0.001
Excess amount of fertilizer due to irrigation (kg)	25.96 (18.679)	19.87 (16.459)	28.52 (19.163)	0.121

Source: Author's calculation from field survey.

Note: This table reports farmers' irrigation and energy source profiles. Only three solar-user farmers own a pump, which they do not use for irrigation currently. Therefore, pump purchase period, purchase cost, and maintenance cost, these variables are not reported group-wise. In the case of the previous source of irrigation energy, no farmer is found in the transition category of diesel to electricity source. Means and standard deviations (in parentheses) are reported for numeric/scale variables and binary and categorical variables are reported in percentage frequency of the 'yes' response/category. Units of variable measurement are in parentheses in the first column. A significant *p*-value (i.e., less than at least 0.10) indicates that solar and non-solar using farmers differ in that category.

The average pump capacity is 10.07KW and solar pumps' capacity is above the average (12.88KW). Similarly, solar pumps' average length of pump-head (46.67 meters) is above the average length (36.72 meters). Farmers' land is on average 193.38 meters away from an irrigation pump and 1566.77 meters away from a water source. Solar pumps (2298.64 meters) can lift and channel water from a significantly longer distance than non-solar pumps (834.90 meters). More than 65.50% of the farmers used different energy modes in the past 10 years, and among them switching from diesel is the largest (89.50%). Overall, the energy switch percentage is three times higher for solar users than for non-solar users. The average experience of using solar energy is 4.43 years. In the case of water sources, most farmers use groundwater (80.63%). Farmers use surface water reservoirs (18.63%) as well as both types (0.75%). Solar farmers use surface water sources while most non-solar farmers extract groundwater. Only a small fraction of farmers (6.63%) requires excess chemical fertilizers because of irrigation and on average, they use an excess of 26 kg of fertilizer per crop. Non-solar farmers (28.52kg) apply more fertilizers than solar users (19.87 kg).

Investment behaviour

In the past 15-20 years, only 17.25% of the farmers planned or started any investment (Table 2.4.8). These investments include both agricultural and non-agricultural types. The average investment period is 10.82 years. Solar users (11.79 years) have longer experience in this regard than non-solar users (9.85 years). However, groups do not differ significantly. Among the farmers who have previous or current investments, 79% of them performed economic calculations beforehand. For the type of economic calculations, most farmers performed cost-related calculations (76.80%). Farmers also performed risk (31.19%) and payback timing (52.55%) related calculations.

Impacts of extreme climate events on production

Most farmers (91.50%) experienced crop loss in the past 10 years (Table 2.4.9). In terms of frequency, 2.61 times on average farmers lost partial or full loss of crops to the extreme climate event(s). These extreme events include droughts, floods, storms, thunderstorms, cyclones, landslides, excessive rainfall, fogs, and sleets. Farmers mostly suffered from crop loss because of floods (43.85%), storms (46.04%), excessive rainfall (45.35%), and sleets (46.58%).

Table 2.4. 8 Farmers' investment behaviour.

Variables	Full sample Mean (Std. dev.)/ percentage (yes)	Solar Mean (Std. dev.)/ percentage (yes)	Non-solar Mean (Std. dev.)/ percentage (yes)	*p*-value of difference
If planned/started any new business in last 5-10 years (% yes)	17.25	17.25	17.25	1.000
The investment period (years)	10.82 (9.997)	11.79 (10.803)	9.85 (9.094)	0.255
If perform economic calculations before investment (% yes)	78.99	73.91	84.06	0.145
Type of calculations (% yes)				
If perform any cost-related calculations	76.80	70.97	82.54	0.127
If perform any risk calculations	31.19	27.45	34.48	0.433
If perform any payback period-related calculations	52.55	50.00	55.07	0.556

Source: Author's calculation from field survey.
Note: This table reports farmers' investment experience and related behaviour. The sample size for 'the investment period' and 'if perform economic calculations' is 138 (17.25% of the full sample). Means and standard deviations (in parentheses) are reported for numeric/scale variables and binary and categorical variables are reported in percentage frequency of the 'yes' response/category. Units of variable measurement are in parentheses in the first column. A significant *p*-value (i.e., less than at least 0.10) indicates that solar and non-solar using farmers differ in that category.

Table 2.4. 9 Farmers' crop loss due to extreme climate events.

Variables	Full sample Mean (Std. dev.)/ percentage (yes)	Solar Mean (Std. dev.)/ percentage (yes)	Non-solar Mean (Std. dev.)/ percentage (yes)	*p*-value of difference
Experience any crop loss (% yes)	91.50	90.50	92.50	0.311
Partial or full crop loss (number/times)	2.61 (1.278)	2.52 (1.248)	2.71 (1.302)	0.043
Extreme climate events (% yes)				
Drought	7.90	8.25	7.30	0.526
Floods	43.85	46.68	41.08	0.127
Storms	46.04	44.20	47.84	0.324
Thunderstorms	4.92	5.52	4.32	0.453
Cyclones	0.25	-	0.50	-
Landslides	0.13	-	0.25	-
Excessive rainfall	45.35	47.51	43.24	0.246
Fog	2.32	2.48	2.16	0.771
Sleet	46.58	46.96	46.27	0.840

Source: Author's calculation from field survey.
Note: This table reports farmers' experience of crop failure due to extreme climate events. Crop failure statistics (categories) are calculated for the farmers who experienced a failure. Only 8.50% of the farmers did not lose crops to climate extreme event(s) in the last 10 years. The study area does not include any hilly areas where landslides frequently occur, hence the lowest frequency is observed. Similarly, cyclones are also rare in the study area. Means and standard deviations (in parentheses) are reported for numeric/scale variables and binary and categorical variables are reported in percentage frequency of the 'yes' response/category. Units of variable measurement are in parentheses in the first column. A significant *p*-value (i.e., less than at least 0.10) indicates that solar and non-solar using farmers differ in that category.

Perception of irrigation energy sources

Farmers' general perception is that solar energy should be preferable to fossil (Table 2.4.10). More than 76% of the farmers have this perception. However, groups differ significantly in this matter. Among the reasons for retaining this preference for solar over fossil, the most perceived is that fossil burning increases environmental damage (87.02%). In decreasing order, the other reasons behind solar preference include 'solar does not harm environment' (67.98%), 'solar energy is not wasted' (66.83%), 'the next generation will not face any energy shortage' (58.94% and groups differ), and 'solar ensures an efficient water use (39.24% and groups differ). The reasoning order does not vary between solar and non-solar users. Most farmers perceive that while using energy both economic and environmental sustainability are jointly valuable (62.38%) (Table 2.4.11). The economic benefit is valuable to 27% of the farmers. A very negligible fraction (1.50%) perceives that environmental sustainability is exclusively valuable. In addition, 8.13% of the farmers do not retain any perception of how to value energy use.

Table 2.4. 10 Farmers' general perception of solar energy.

Variables (% yes)	Full sample	Solar	Non-solar	*p*-value of difference
If solar is preferable to fossil	76.13	89.00	63.25	0.000
Why preferable				
Fossil burn increases environmental damage	87.02	86.51	87.74	0.656
Energy is not wasted	66.83	69.10	63.63	0.158
The next generation will not face any energy shortage	58.94	65.45	49.80	0.000
Solar ensure efficient water use	39.24	42.70	34.39	0.038
Solar does not harm the environment	67.98	66.29	70.35	0.290

Source: Author's calculation from field survey.

Note: This table reports farmers' perceptions of solar preference over fossil energy. In the full sample, 15.38% of farmers do not prefer solar to fossil while 8.50% of the farmers do not have any perception. Categorical perceptions are calculated for farmers who prefer solar energy. In all categories, the solar group's perception is above the average while the non-solar group is below the average. This may be due to the impact of solar energy use. All variables are reported in percentage frequency of the 'yes' response. A significant *p*-value (i.e., less than at least 0.10) indicates that solar and non-solar using farmers differ in that category.

Table 2.4. 11 Farmers' valuation and sustainability perception while using energy.

Variables (% yes)	Full sample	Solar	Non-solar	*p*-value of difference
What is more valuable				
Economic benefit	27.00	21.00	33.00	0.000
Environmental sustainability	1.50	2.00	1.00	0.245
Both are equally valuable	62.38	73.50	51.25	0.000
None of them	1.00	-	2.00	-
No perception	8.13	3.50	12.75	0.000
If the used energy source is sustainable	66.63	92.50	40.75	0.000
Why use solar energy				
Time-saving and less system pressure		57.25		
No installation personally		51.00		
Less labor cost		74.25		
Fewer chemical inputs		3.25		
Low irrigation cost		79.00		
Environmentally safe		83.00		
No harm to human health		46.00		
Less water pollution		58.25		
Better crop health		17.75		
Increase in crop quantity		40.25		

Source: Author's calculation from field survey.

Note: This table reports farmers' valuation while choosing an energy source and reasons for using solar energy. For the latter, only solar farmers answered. All variables are reported in percentage frequency of the 'yes' response. The value for 'if used energy is sustainable' for the non-solar group i.e., 40.75% is the perception combining diesel and electricity users. However, 7.13% of diesel users perceived that their source is sustainable. A significant *p*-value (i.e., less than at least 0.10) indicates that solar and non-solar using farmers differ in that category.

Farmers (66%) also understand if the energy they are currently using for irrigation is sustainable or not. Notably, more than 90% of solar users possess the sustainability perception of solar energy, while 40% of non-solar users also perceive that their energy source is sustainable. Among solar users, the prime reasons for using solar irrigation systems are related to i) energy security and resource sustainability, i.e., 'environmentally safe' (83%), 'no harm to human health' (46%), 'less water pollution' (58.25%), 'increase in crop quantity' (40.25%), ii) cost-efficiency, i.e., 'low irrigation cost' (79%) and 'less labor cost' (74.25%), and iii) management, i.e., 'time-saving and less system pressure' (57.25%) and 'no installation personally' (51%).

Crop residue management

Farmers manage crop residues in several ways (Table 2.4.12). Most farmers (67.50%) use crop residues as animal fodder. Some of them (15.88%) sell the residues. Only 3.75% and 4.25% of the farmers respectively decompose and use them as cooking fuel.

In unsustainable approaches, farmers also burn the residues on the field (5.63%) and do nothing with them (3%). Crop residue management methods do not vary between solar and non-solar users. However, a higher proportion of non-solar users burn residues on the field compared to solar users.

Table 2.4. 12 Farmers' crop residue management.

Variables (% yes)	Full sample	Solar	Non-solar	*p*-value of difference
Decompose	3.75	3.00	4.50	0.264
Sell	15.88	15.50	16.25	0.772
Cooking fuel	4.25	5.25	3.25	0.161
Animal fodder	67.50	67.75	67.25	0.880
Burn on the field	5.63	4.50	6.75	0.167
Do nothing	3.00	4.00	2.00	0.097

Source: Author's calculation from field survey.
Note: This table reports farmers' crop-residue management methods. Farmers are asked about an approach that they mostly follow for managing crop residue. However, it is also possible that they use multiple approaches. All variables are reported in percentage frequency of the 'yes' response. A significant *p*-value (i.e., less than at least 0.10) indicates that solar and non-solar using farmers differ in that category.

Household waste management

Two major approaches to waste management of farm-households (Table 2.4.13) are proper disposal (60.63%) and decomposition (34.25%). Only 1% of the farmers reuse/recycle/sell the waste. Some farmers throw wastes discretely (2.38%) and do nothing about them (1.75%). Groups do not differ in various waste management approaches. However, solar users dispose wastes more properly than non-solar users do. Non-solar users prefer to decompose more than solar users do.

Table 2.4. 13 Farmer-households' waste management.

Variables (% yes)	Full sample	Solar	Non-solar	*p*-value of difference
Dispose properly	60.63	62.50	58.75	0.278
Decompose	34.25	31.75	36.75	0.136
Reuse/recycle/sell	1.00	1.25	0.75	0.477
Throw discretely	2.38	2.25	2.50	0.816
Do nothing	1.75	2.25	1.25	0.281

Source: Author's calculation from field survey.
Note: This table reports farm households' waste management approaches. Farmers are asked about an approach that they mostly follow for managing household waste. However, it is also possible that they use multiple approaches. All variables are reported in percentage frequency of the 'yes' response. A significant *p*-value (i.e., less than at least 0.10) indicates that solar and non-solar using farmers differ in that category.

Irrigation contract and payments

Most farmers are in a water contract for irrigation and they pay hourly for irrigation (55.38%). Solar farmers use more a crop contract and less a water contract than non-solar users and the difference is significant. The average period of being in the existing contract is 9.34 years. On average, approximately 33 farmers irrigate their lands together using the same system. Solar users have been in the current contract for a lesser period. A larger group of farmers (approximately 43 farmers) can use a solar irrigation system together compared to a non-solar system (approximately 24 farmers). As the roles of irrigation fee payee/payer, there are five categories, namely i) water buyer, ii) water seller, iii) both seller and buyer, iv) pump owner/operator, and v) pump owner who sells water. Most of the farmers purchase water (84.13%) and this frequency is higher in the solar group (97.75%). A small number of farmers are pump owners/operators (7.13%). Only 6% of the farmers who own pumps sell water as well.

Perception of irrigation Contract choice

Most farmers choose an irrigation contract (Table 2.4.15) in which they can receive sufficient water supply (65.25%). The other prime factors include low irrigation cost (56.25%), pump location (46.50%), and good relations with water sellers (21.50%). However, for the solar group, low irrigation cost (84.75%) and sufficient water supply (78%) are the two most determining factors in choosing an irrigation contract. Solar farmers also value pump proximity largely (59.50%). Non-solar users think about water supply primarily and then pump location and irrigation cost. Farmers previously followed a different irrigation contract as well (44.13%) (Table 2.4.16). This frequency is substantially higher for the solar group than for the non-solar group. Most farmers left the previous contract because of high irrigation costs (82.44%). Two other significant reasons behind cancelling the past contract include an insufficient water supply (62.32%) and payment defaults (48.16%). Location of a pump at a longer distance was also among the reasons (20.11%). The order of reasoning is similar for both farmers' groups. However, high irrigation cost was the more compelling reason for the solar group than the non-solar group. The frequency of an insufficient water supply was higher for non-solar users.

Table 2.4. 14 Farmers' irrigation contracts and payments.

Variables	Full sample	Solar	Non-solar	*p*-value of difference
	Mean (Std. dev.)/ percentage (yes)	Mean (Std. dev.)/ percentage (yes)	Mean (Std. dev.)/ percentage (yes)	
Irrigation contract (% yes)				
Water contract	55.38	32.00	78.75	0.000
Crop contract	44.63	68.00	21.25	0.000
Contract period (years)	9.34 (8.96)	4.55 (2.35)	14.13 (10.46)	0.000
Farmers' group size for pump use (number)	33.49 (20.69)	42.66 (10.22)	24.33 (24.09)	0.000
Farmers' group size for water use (number)	36.61 (19.34)	42.66 (10.44)	30.11 (24.05)	0.000
Irrigation charge payer/payee (% yes)				
Water buyer	84.13	97.75	70.50	0.000
Water seller	0.25	0.25	0.25	1.000
Both seller and buyer	2.50	1.50	3.50	0.070
Pump owner/operator	7.13	0.50	13.75	0.000
Pump owners who sell water	6.00	-	12.00	-
Payment mode (% yes)				
Hourly rate	29.63	32.00	27.25	0.142
Entire season	70.38	68.00	72.75	0.142

Source: Author's calculation from field survey.
Note: This table reports farmers' irrigation contracts, payment types, and irrigation user features. In the case of the farmers' group using the same water source, the sample is 772 (there are missing values because 28 non-solar farmers do not know the number correctly). Solar farmers do not own pumps in the study area, hence 'pump owner and water seller' category is blank for this group. Both solar and electrical systems have a pump operator. Means and standard deviations (in parentheses) are reported for numeric/scale variables and binary and categorical variables are reported in percentage frequency of the 'yes' response/category. The units of variable measurement are in parentheses in the first column. A significant *p*-value (i.e., less than at least 0.10) indicates that solar and non-solar using farmers differ in that category.

Table 2.4. 15 Farmers' preference for an irrigation contract.

Variables (% yes)	Full sample	Solar	Non-solar	*p*-value of difference
Irrigation cost is low	56.25	84.75	27.75	0.000
Energy source change	8.13	15.00	1.25	0.000
Good terms with water seller	21.50	24.75	18.25	0.025
Water seller/buyer is a relative/friend	7.13	5.75	8.50	0.131
Sufficient water supply	65.25	78.00	52.50	0.000
Pump proximity	46.50	59.50	33.50	0.000
Farmer is a pump owner/operator	10.88	3.00	18.75	0.000
Following peers	13.75	4.50	23.00	0.000

Source: Author's calculation from field survey.

Note: This table reports farmers' reasons for choosing an irrigation contract. All variables are reported in percentage frequency of the 'yes' response. The energy changes category includes six types: solar to diesel, solar to electricity, electricity to diesel, electricity to solar, diesel to electricity, and diesel to solar. A significant *p*-value (i.e., less than at least 0.10) indicates that solar and non-solar using farmers differ in that category.

Table 2.4. 16 Farmer's reason for changing irrigation contract.

Variables (% yes)	Full sample	Solar	Non-solar	*p*-value of difference
Left the previous contract	44.13	70.75	17.50	0.000
Reasons for leaving the previous contract				
Irrigation cost was high	82.44	84.45	74.29	0.045
Energy source change	3.12	3.89	-	-
Bad terms with water-seller	2.27	2.47	1.43	0.600
Insufficient water supply	62.32	60.78	68.57	0.229
Payment default	48.16	48.76	45.71	0.648
Pump in long distance	20.11	21.20	15.71	0.307

Source: Author's calculation from field survey.

Note: This table reports farmers' reasons for changing the previous irrigation contract. The reasoning variables are calculated for the sample of farmers who left the previous contract (i.e., 353 farmers). The energy changes category includes six types: solar to diesel, solar to electricity, electricity to diesel, electricity to solar, diesel to electricity, and diesel to solar. In this category, only solar farmers responded, hence the other cell is blank. All variables are reported in percentage frequency of the 'yes' response. A significant *p*-value (i.e., less than at least 0.10) indicates that solar and non-solar using farmers differ in that category.

2.5 Research framework: the coordination matrix

The main analysis of this research has three parts in three essays. In these essays, this research uses two choice experiments and a natural experiment approach to evaluate farmers'- i) financial understanding (Chapter 3), ii) pro-environmental behaviour (Chapter 4), and iii) cooperation (Chapter 5). The following Table 2.4 presents the coordination matrix of the research design. It is a matrix of outcome variables, data sources, and methods of analysis of the three essays.

Table 2.5 The coordination matrix of this research.

Essays	Outcome variables	Data source	Methods of analysis
a. Farmers' financial understanding	i. Forward-looking behaviour ii. Calculation ability iii. Risk-taking levels	Choice experiment and field survey data from 400 solar and 400 non-solar farm households	Sample t-test, Logit regression Ordered logit regression Mean regression ROC analysis
b. Farmers' pro-environmental behaviour	i. Pro-environmental behaviour ii. Environmental motivations iii. Consistency of motivations	Choice experiment and field survey data from 400 solar and 400 non-solar farm households	Sample t-test Logit regression Multinomial logit regression ROC analysis
c. Farmers' cooperation in cultivation	i. Irrigation contract ii. Irrigation group iii. Irrigation length iv. Irrigation efficiency	Natural experiment from field survey data from 400 solar and 400 non-solar farm households	Sample t-test ANOVA Density and quantile distributions Logit regression Mean regression Quantile regression Instrumental variable regression

Source: Author's preparation.
Note: This table presents the coordination matrix of the research designs of the three main parts of this thesis. In all the three following parts, the empirical strategy is to compare outcome variables for solar and non-solar user-farmers.

2.6 Conclusion

This chapter has described the background of the broader study area for agriculture and the relevant resource use statistics. It has set up the contextual and scenario analyses of the solar irrigation systems in Bangladesh agriculture. This chapter also has discussed the multi-stage process for the selection of the study area including high and low solar adoption districts. Then the illustration of the sample selection process and a detailed discussion of farm household characteristics followed. Finally, this chapter has presented an overview of the research design in the coordination matrix. The following chapters discuss the details of this design including conceptual frameworks, experimental designs, and measurements of outcome variables and findings of the three essays.

Chapter 3

Financial understanding of renewable technology adopters

3.1 Introduction

Renewable technology is one of the promising mitigation strategies for energy diversification and substitution processes. However, both processes are slow possibly owing to policy pitfalls and attitudes toward technology switches. Technology switch involves a comparative evaluation and uncertainties. When technology use depends on a least-cost decision, saving energy is a secondary concern (Wang et al., 2020). It is reasonable from a user's perspective. Adoption decision is crucial in new technology cases, because users may disregard the benefits of the upfront investment and consider the payback timing (De Groote and Verboven, 2019). Rational decision-making requires optimality, yet various intuitive factors often influence adoption behaviour. Particularly in renewable technology, decision-making is complicated because of- i) long-term investment requirements, ii) insufficient knowledge sharing, and iii) lack of motivation. Cognitive limitations even restrict the understanding of these conditions. Therefore, economic and environmental valuation approaches do not sufficiently explain adoption behaviour. This study argues that technology-use explains cognitive financial understanding and together they can drive sustainable choices.

The decision-making process of sustainable technology mostly uses return expectations, risks and environmental assessments (Farrin and Miranda, 2015; Reise et al., 2012; Salazar et al., 2019). In this respect, whether a technology reduces risks or ensures potential gains is the most explored condition. Regarding this, two major confounders are information and incentives. Accessibility of both information and financial products received much attention. Farrin and Miranda (2015) observed that insurance increases high-yield technology adoption. Flory (2018) demonstrated that information influences savings behaviour, increasing fertilizer expenditure and crop income. However, these results do not address whether adoption decisions cause the use of information and incentives. The relationship between technology adoption and farm welfare is not always straightforward. If information dissemination is costly, peer farmers would not wish to share (Balew et al., 2022). There are even alternative scenarios regarding farmers' financial inclusion. Goodwin and Piggott (2019) showed that yield risk increases for insured farms that adopted genetically modified seeds. Insurance access decreases the use of risk-mitigating technology in Salazar et al. (2019). In such cases, financial products involve uncertain outcomes, and hence choice resorts to individual reasoning. Referring to Salazar et al. (2019), another important aspect might be the timing of acquirement, i.e., whether a financial product is accessible before or after adopting any new technology. The precision of information (Yu and Hendricks, 2020), and different approaches to information dissemination (Van Campenhout et al., 2020) may contribute to this matter. Potential adopters should understand the information content, which includes technology features and monetary incentives. Consequently, they can perceive the necessity of learning and the process of technological change. It is important to note that the pace of adopters' learning is slower than that of environmental changes and this makes decision-making more variable (Foramitti et al., 2021). The authors also demonstrated that if adopters cannot evaluate the acquired information, decisions become sub-optimal. Such decision-making results from cognitive limitations. One established parameter reducing cognitive limitations is financial literacy. Theoretically, financial literacy is an accomplishment in financial matters through *knowledge*, *ability*, *aptitude*, *skill,* and *confidence* (Remund, 2010). Financial literacy induces borrowing decisions, the use of financial products, and risk portfolio choices (Magni, 2009). A decision-making process that uses financial literacy is holistic by nature. Potential investors rely on financial information even without securing a sufficient wealth base (Robb et al., 2015). Financial literacy coupled with a perception of high returns leads households to be risk-takers (Bianchi, 2018). Thus, an understanding of financial matters elicits the ability to process information separately. Generally, decision-making in agriculture is crucial owing to various structural risks in input mix and harvest uncertainties. Agriculture involves multi-stage input choices in one production round. Farmers need to evaluate each input and accordingly plan on the best use of resources. In this respect, we observe that past studies largely focus on productivity gains and efficient water use[7]. However, there is not sufficient evidence of farmers' vision and precision regarding renewable or any sustainable technology adoption.

This study explores the relationship between farmers' financial understanding and their solar irrigation technology adoption. In solar irrigation projects in Bangladesh, farmers either pay for service or take loans to procure equipment. In any of the cases, farmers do not make down payments or investment decisions for system installation. This implies that farmers would own the system after repayment. Farmers' solar adoption decision is less likely to be guided by financial optimization. Therefore, I use the bounded rationality framework to develop choice experiments with hypothetical scenarios and to estimate the relationship between solar irrigation and farmers' financial understanding. Bounded rationality theory suggests that reasoning level, information processing ability, and timing affect economic decisions (Conlisk, 1996). That is why, financial understanding uses three parameters, i.e. forward-looking behaviour, calculation ability and risk-taking behaviour. I test three hypotheses. These

[7] Some of the notable studies in different efficient irrigation technology use and management include Alauddin and Sarker (2014), Genius et al. (2014), and Emerick et al. (2016).

are- i) solar irrigation users are financially more forward-looking than non-users; ii) solar irrigation users are more capable of performing calculations and understanding opportunity costs; and iii) solar irrigation users are more capable of developing risk-taking behaviour. By utilizing choice experiments, I estimate farmers' stated responses toward products (differentiated by risk and return) for each parameter of financial understanding. Farmers choose between a short-run/low-risk-return option and a long-run/high-risk-return option. The probability models estimate the correlations between solar irrigation users and i) financially forward-looking behaviour; ii) the understanding of calculation and opportunity cost, and iii) risk-taking levels.

This chapter proceeds as follows. Section 3.2 discusses the theoretical approach to financial understanding and renewable technology adoption behaviour. Section 3.3 provides a detailed description of the experimental design, empirical models, and sample characteristics, followed by Results and discussions in Section 3.4. This chapter is concluded in Section 3.5 by providing a summary of the results and implications.

3.2 Theoretical approach to financial understanding and renewable technology adoption

This study assumes that preference depends on individual reasoning ability to understand features of choices. Farmers' stated preferences may or may not reflect their irrigation technology use. The experimental design in this study at each level of financial understanding requires two distinctive choices based on investment types by risk and return. To build the framework, this study first assesses the factors determining sustainable technology adoption and then analyses investment decision-making. Among all factors, the focus is on the two most discussed issues in adoption literature, i.e., information and finance. The discussion utilizes the notion that incentives, either monetary or non-monetary, are not sufficient for adoption decisions. Available literature also suggests that mostly information and financial constraints impede adoption[8]. That is why, information access and financial inclusion received much attention in technology diffusion. Improved information enhances confidence in technology use (Doran et al., 2020) and helps mitigate production-related vulnerabilities (Emerick et al., 2016). Mukherjee (2020) observed a positive link between improved seed use and institutional credit. Similarly, Ojo and Baiyegunhi (2020) found that credit, extension services, and organizational membership change cropping strategies positively. Often farmers rely on established and institutional guidelines to make adoption decisions. Farmers positively respond to institutional awareness programmes (Quiroga et al., 2020) and peer demonstrations (Balew et al., 2022). Gao et al. (2019) observed that intended adoption and actual adoption vary with information distribution sources. They showed that institutions improve adoption, while peers reduce the intensity and they do not influence green technology preference. Insurance knowledge does not increase the demand for all types of insured products (Janzen et al., 2021). Fafchamps et al. (2020) in their incentive-based experiment, also found that the likelihood of adoption increases if only trained farmers demonstrate about it to their peers. Thus, previous studies give mixed evidence of financial information and products. Even access does not ensure its utilization and hence adoption. Information loses its credibility to limited extension services.

In sustainable adoption literature, several studies analysed farmers' attitudes toward adoption and economic risks. For example, He et al. (2019) showed that rural users who want to avoid investment risk and economic loss, do not purchase and use

[8] e.g., Alauddin and Sarker (2014); Doran et al. (2020); Emerick et al. (2016); He et al. (2019); Karlan et al. (2014); Liu et al. (2019); Ojo and Baiyegunhi (2020); Quiroga et al. (2020); and Villamayor-Tomas et al. (2019).

any energy-efficient technology. Risk-averse farmers are less likely to make biogas investments (Reise et al., 2012). Risk-averse farmers are also less likely to use modern inputs (Mukasa, 2018). The author additionally argued that farmers assume production risks in such cases and perceive that modern inputs would not guarantee a higher return. In contrast, Farrin and Miranda (2015) demonstrated that risk-averse farmers are more likely to adopt high-yield technology if they have access to contingent credit options. Barrett et al. (2020) observed similar results for trained *persistent adopters* using rice intensification methods. Ito et al. (2018) showed that *economic incentive* has a stronger effect on efficient energy use than *moral suasion*. They used high electricity charges for 'economic incentive' households and persuasive energy conservation messages for 'moral suasion' households. Their findings reflect users' capability of cost calculations. However, this study examined seasonal household appliances (e.g., heaters in winter and air conditioning in summer) and predetermined weekdays. Household electricity usage is comparatively low on working days. Thus, financial incentives or disincentives cannot sufficiently explain sustainable behaviour. Previous finance-related studies demonstrated that financial inclusion improves if users have finance-related knowledge and literacy, and risk perception (e.g., Bianchi, 2018; Flory, 2018; Robb et al., 2015; Salazar et al., 2019). Financial education teaches planning, balance, and diversification of finance (Kaiser and Menkhoff, 2022). Lührmann et al. (2018) observed that financial education affects time preferences in investment decisions and eventually users' financial condition. Ma and Shi (2015) demonstrated that there is an interplay of experience (both personal and peer) and thus learning efficiency increases adoption. The authors explained that adopters primarily use the information on potential benefits and the experience in the following periods helps their decision-making. Adopters perform current cost calculations and net gain over multiple periods. The financial market and investment framework are also essential in decision-making. Karlan et al. (2014) found that uninsured risks restrict farmers' investments. The authors argued that agricultural finance markets are not structured and farmers lack trust in financial services and products. To trust providers, users can apply financial knowledge (Cruijsen et al., 2021) as well as personal financial inclusion (Rahman et al., 2020). Efficiency in decision-making thus advances with the applicability of information and experience. The reason is that forward-looking farmers are open to innovation (Cullen et al., 2020), and able to calculate returns in a dynamic setup (Ma and Shi, 2015). I draw two conclusions here. Apart from economic valuations, i) attitude toward technology and financial products explains adoption, and ii) knowledge increases adoption in both cases. It is possible that personal understanding primarily triggers adoption decisions and then the acquired knowledge facilitates it. Financial understanding thus can be endogenous to the choice of technology that requires investment knowledge and experience. The available evidence does not sufficiently demonstrate if individual understanding and knowledge reflects adoption decision.

Behavioural patterns are diverse for myopic and forward-looking investors/producers, risk-takers, and risk-averse users (e.g., Cullen et al., 2020; Farrin and Miranda, 2015; Yu and Hendricks, 2020). The nature of risk apprehension and financial knowledge often dominates technology adoption behaviour. Robb et al. (2015) argued that subjective knowledge (perceived knowledge) dominates objective knowledge (actual knowledge) in financial investment. In agriculture, when production risk is beyond users' control due to a variable climate, adoption follows intuition. For example, a positive perception of fuel substitution and investment profile encourages a green switch (Pleeging et al., 2021). Subjective climate risk perception induced the uptake of soil fertility management in Krah et al. (2019). However, Abebe et al. (2022) showed that farmers' potential and actual adaptation choices vary over time, yet high climate risk perception decreases actual risky adaptations. Freudenreich and Musshoff (2022) demonstrated that previous yield loss does not alter risk-averse behaviour, implying no association between objective and subjective risk perception. It is possible when production loss is a probability or self-reported. It is more difficult to control the cost variability of modern technology than to assume yield impacts (Mukasa, 2018) and even to receive compensation (Yu and Hendricks, 2020). According to the *Prospect theory* of Kahneman and Tversky (2013), risk-averse behaviour is the preference for a prospective option over a risky one. This implies that decision-making associated with risk is circumstantial and subjective in different representations. Previous results also suggest that investment decisions by risk and return expectations are subjective and may change with experience. Even expectations and experience are not constant. More importantly, perception varies with the nature of technology, institutional support, investment experience, and risk intensity.

The existing literature shows that sustainable technology users outperform in information use and investment interpretation, yet it does not clarify users' quality in showing such performance. Compared to other environmental resources, renewable energy, e.g., solar and wind, are more amenable to a bounded evaluation because a decision-maker cannot control the sources. In such cases, the willingness-to-pay method may explain how an individual would value costs and benefits (Halkos and Matsiori, 2014). However, as Conlisk (1996) pointed out, there is a difference between willingness-to-pay (WTP), and willingness-to-accept (WTA), and valuation based on the former cannot be reliable. Even in this case, reasoning generates a larger WTP (Chauhan and Dey, 2020). An income effect in addition may alter scenarios. For instance, in Bakkensen and Schuler (2020) households pay more for both renewable and fossil uses if their assets increase. Thus particularly in renewable technology adoption, the classical rationality assumption is not sufficient to explain behaviour. This study uses the bounded rationality notion, which shows that cognitive ability removes the loopholes and anomalies of rational decisions (Conlisk, 1996; Kahneman, 2003). The bounded framework is multidimensional encompassing *attention, information representation,* and *elaboration* and *memorization* (Frör, 2008, p. 572). Motivated by this, the following choice experimental design uses subjective and objective options by risk-return profiles. The idea is that farmers' cognitive ability in interpreting an option explains their irrigation technology adoption behaviour. The experimental setup uses financial understanding parameters as proxies for cognitive ability. Therefore, the empirical strategy is to predict the correlation between financial understanding and solar technology adoption through farmers' stated choices.

3.3 Methods and research design

3.3.1 Experimental design

Both distant and recent past literature demonstrates that financial literacy contributes to understanding financial matters and making good investments (Remund, 2010; Gaudecker, 2015; van Der Cruijsen et al., 2021). Referring to Remund (2010, pp. 279-285), four aspects of the conceptual definition of *financial literacy*, namely *knowledge, ability, aptitude,* and *skill* are used to design the financial understanding choice experiment. Each aspect has distinctive yet interrelated features. Remund (2010) explained that knowledge and ability are distinguishable based on their applicability; aptitude reflects application ability, and skill links aptitude and actual choices. The author further demonstrated that decision-making in the short-run and planning for the long-run determine the level of financial literacy through an interplay of various aspects of literacy and experiences. In this design, I utilize knowledge, ability, and aptitude components to construct all choice options, and the stated choices reflect skill. However, the strategy is not to estimate these components directly, financial understanding is operationalized instead of financial literacy. I do not use any real choice scenario and therefore I exclude the confidence component. I develop three mutually exclusive choice experiments to estimate the financial understanding of solar irrigation use. For each parameter, one subjective-type binary choice set is given and then objective-type (both binary and multiple types) questions are constructed. Three parameters, namely financially forward-looking behaviour, ability to calculate returns, and risk perception can jointly measure financial understanding.

The merit of a hypothetical choice experiment is that its players are straightforward while making choices (Kahneman and Tversky, 2013). For the subjective choices, a *classifier model* (Conlisk, 1996, pp. 676-682) is followed where each participant is given two symbolic options to choose from in three discrete levels. A participant chooses one option separately at each level. In this experiment, similar sets of choices are given to solar irrigation users, and non-solar irrigation users. Subjective choice-making can be different from objective one (Robb et al., 2015). Thus, each subjective choice experiment is followed by money-related questions objectifying the outcomes of interest. Often in a bounded rationality framework, there is a possibility of overestimation in the absence of real monetary incentives (Reise et al., 2012). This may be true in the case of hypothetical incentive-based choice experimental designs. Participants do not receive any real money or incentives, so their perceptions remain unbiased. I use thematic subjective choice sets and quiz-type money-related questions. Farmers themselves do not write their choices and answers in the forms. Instead, the selected and trained surveyors use a 20-minute window (5 minutes each for the first two levels and 10 minutes for the last level) to complete the experiment. I do not use any fixed timing for the experiment, yet our experiment is less likely to be affected by response bias. Farmers are not informed of choice constructions, hence there is no *carryover effect* (Yang et al., 2018). I also ask the feedback for making each choice at the end of the experiment. However, this does not allow them to think about the interrelations between games and related questions. The stated choice may be an uncertain preference leading to a hypothetical bias. As Loomis (2011) explained, I use feedback on choice-making as an *ex-post* approach to reduce bias. Farmers' feedback is similar to the framework I use in choice construction. The assumption is that the same explanatory variables explain the stated choices and the associated feedback. Thus, I do not estimate the feedback. The discussion on correlations uses their feedback. Finally, to identify control variables, I use the standard of living and provisions at the household and farm levels. Literature shows a great deal of heterogeneity in socio-demographic and farm characteristics including investment behaviour that impact sustainable behaviour. For example, Liu et al. (2019) demonstrated that young, educated, and trained farmers are likely low-carbon users. In addition, De Groote and Verboven (2019) observed that the adoption of a new technology varies greatly with household heterogeneity in income, education, citizenship and population density. Therefore, this study uses a survey with a structured questionnaire asking about households' socio-demographic characteristics, farm characteristics, input cost and output revenue, and institutional and information accessibility.

Financially forward-looking behaviour experiment: Forward-looking behaviour indicates visions about problems that have long-term horizons and the related solutions are dynamic (Pot et al., 2019). I operationalize financially forward-looking behaviour as the *knowledge* and *ability* regarding long-run investment. The following choice set is given and questions are asked:

Subjective choice (props)	Objective choice (questions)
Two boxes are shown to a participant. One box contains one big ball and another box contains multiple small balls. A. Which box do you choose?	B. Which option will you choose between BDT100 and 1/6th of BDT100 for 7 days? C. What will you choose between BDT100 and 1/6th of BDT100 for the first 3 days and 1/3rd of BDT100 for the remaining 4 days?

Each choice involves a return differentiated by its timing, namely a one-period return and returns in multiple periods. I use different rates for the second option in question (C) to observe if the choice changes perceiving a higher return in (C) than offered in question (B). I calculate a forward-looking score based on choosing a multi-period option every time in subjective box choices and objective choices. I test the following hypothesis:

H3.1: farmers using solar irrigation are more likely to choose multi-period return choices both subjectively and objectively, i.e., solar users are financially forward-looking.

Understanding calculation and opportunity cost experiment: To examine whether farmers understand economic cost calculations and make a choice accordingly, farmers choose between boxes assigned with monetary values. The details are as follows:

Subjective choice (props)	Objective choice (questions)
Two boxes are shown to the participant. One is transparent containing one ball and the other is solid containing five small balls. The transparent box contains one ball worth BDT100 and the solid box contains small balls worth BDT20 each. (Participant does not know how many balls there could be in the 2nd box, and the value of the two boxes is the same.) D. Which box do you choose?	E. (If the participant chooses the 1st box) The value of each ball in the 2nd box increases to BDT25, will you switch to the solid box? (The value of the 1st box remains the same.) F. (If the participant chooses the 2nd box) The value of the 1st box increases to BDT125, will you switch to the transparent box? (The value of the 2nd box remains the same.)

Balls in each box are marked with hypothetical monetary values. The transparent box represents “money now”, because the amount of money is visible to farmers. The solid box represents “money later”, because farmers can only assume the total amount of money by taking a glance at one ball’s worth. Surveyors inform farmers here what boxes represent. The rationale is to observe deviations in choice-making if any economic matter is involved. The notion of opportunity cost can be generally subjective by perceiving no actual monetary gain or loss. For this reason, the total value of the two boxes remains the same at this stage, implying zero opportunity cost in monetary terms. If a participant chooses the solid box, he/she pulls each ball and completes the stage. That means ‘money later’ option resembles a longer payback period and the invisibility feature reflects uncertainty. There is a tendency to assign higher values to goods to be given up than acquired when there is no risk involved (Kahneman, 2003; Thaler, 1980). Therefore, in the objective choice questions, a higher value to the forgone or unselected box is assigned than the boxes shown in the initial stage. Farmers get the information that in the choice sets E or F the value of the selected box (in choice D) remains the same. The motivation is that it may show farmers’ *aptitude* to understand opportunity costs through switching to a higher value box. In this procedure, the following hypothesis is:

H3.2: farmers using solar irrigation are more likely to choose the ‘money later’ option and switch to a higher value box, i.e., solar users understand calculation and opportunity costs.

Risk perception and risk-taking behaviour experiment: In this experiment, the motivation is to evaluate farmers’ *knowledge* of risk and the associated return and their *aptitude* level in terms of risk-taking behaviour. In experiments, risk attitude varies with choices given to the participants as Kahneman (2003) explained. Therefore, subjective and objective choices use completely different options.

The details are as follows:

Subjective choice (props)	Objective choice (questions)
G. It is possible that one of the boxes containing balls got a hole at the bottom. Which box do you choose? H. There is a hole in the box containing small balls, so if you take it you will lose some. Which box do you choose?	I. For which reward will you participate in a lottery game? i. do not want to participate ii. a sure gain of BDT50 iii. 50% chance of winning BDT100 iv. 25% chance of winning BDT150 J. For which reward will you participate in a lottery game? i. do not want to participate ii. 50% chance of winning BDT100 iii. 25% chance of winning BDT150 K. For which reward will you participate in a lottery game? i. do not want to participate ii. 75% chance of winning BDT50 iii. 50% chance of winning BDT100

On the subjective side, I observe farmers' risk perception if there is a risk probability (choice G) and there is a sure risk (choice H). In the objective-type questions (choice sets I, J, and K), different financial rewards are mentioned in a hypothetical lottery game. These attributes measure farmers' risk-taking behaviour. The rewards are based on the winning probability at different risk-return levels. For instance, in choice (I) option (i) signals risk-averting behaviour, (ii) shows no risk but a sure gain, option (iii) is a low risk-return level, and option (iv) offers a high risk-return. Risk-taking behaviour may change if there are no known economic gains. For this purpose, we change reward sets in choices (J) and (K) removing the "sure gain" option. In this experiment, the hypothesis is tested as follows:

H3.3: farmers using solar irrigation are more likely to choose either low risk-return or high risk-return options, i.e., solar users are risk-takers.

3.3.2 Models

3.3.2.1 Construction of outcome variables

Financially forward-looking behaviour

The forward-looking option, i.e., small balls and multiple periods (7-day) return option is coded 1 and 0 otherwise. In choice A, the code 0 is for the big-ball box, and accordingly, in choices B and C, the code is 0 for the option, return in a single period. Then the forward-looking behaviour is the summation of subjective and objective choices. If a farmer is perceptive of small balls, the stated choice may explain his/her cognitive ability. Farmers may understand that a box of small balls represents a higher return in multiple periods. Similarly, they may understand that 7-day fractional returns are higher than the single-period option. Therefore, if the index number is higher, a farmer's forward-looking behaviour improves. The codes of the forward-looking order are as follows, $1 = not\ forward - looking$, $2 = low\ level\ of\ forward - looking$, $3 = medium\ level\ of\ forward - looking$, and $4 = high\ level\ of\ forward - looking$.

Understanding calculation and opportunity costs

I measure farmers' subjective understanding of return calculation giving the binary choice of a box worth some monetary value. In each choice, I code the 'money now' option as 0 and the 'money later' option as 1. For the objective part, I code 1, if a farmer wishes to switch choices to a higher value box (i.e., solid box in the choice set E and transparent box in the choice set F), and 0 otherwise. I also combine the choices in D and E/F to examine if they have an understanding of calculation and opportunity costs. For this parameter, the assumption is that the transparent box's visibility feature could influence choice-making. Thus, it is possible to determine the combined understanding variable either at the subjective or objective level.

Risk perception and risk-taking behaviour

In the subjective risk perception level, code 1 is for the risky box (i.e., the possibly broken box of small balls in set G and the surely broken box of small balls in set H) and 0 otherwise. The code is 0 for the big-ball box, with no risk attached. Then, the rewards in the lottery-type objective questions evaluate farmers' risk-taking behaviour. For choice level (I) the order of risk-taking behaviour is coded as follows: $1 = no\ participation/no\ risk$, $2 = participation/sure\ gain$, $3 = low\ risk\ and\ return$ and $4 = high\ risk\ and\ return$. For choices (J) and (K), we code three levels, namely $1 = no\ participation/no\ risk$, $2 = low\ risk\ and\ return$ and $3 = high\ risk\ and\ return$. For a robustness check, a continuous risk score is constructed by adding 2 attributes of subjective risk perception and 3 attributes of objective risk-taking behaviour. The minimum value of this index is 3 (if a participant chooses unbroken boxes in choice sets G and H, and then chooses not to participate in choice sets I, J, and K), and the maximum value is 12 (if a participant chooses broken boxes in choice sets G, and H, and then chooses the highest risk-return options in choice sets I, J, and K).

Financial understanding

Since choice experiments are mutually exclusive, behaviour in each step remains unique. The understanding of financial matters can also be a comprehensive and consistent behaviour. It is a combination of forward-looking choices (3 attributes), understanding calculation and opportunity cost (any between subjective and objective attributes), and risk perception and behaviour choices (5 attributes). Thus, farmers can score a minimum of 3 and a maximum of 16. The following Figure 3.1 shows the channels of financial understanding measurement.

Table 3. 1 Construction and measurement of financial understanding.

Forward-looking behaviour	Understanding calculation and opportunity costs	Risk perception and risk-taking behaviour
Subjective: Big ball (0) vs small balls (1) 1 attribute	Subjective: Money now (0) vs money later (1) 1 attribute	Subjective: i) Big ball (0) vs a possibly broken box of small balls (1) and ii) Big ball (0) vs a surely broken box of small balls 2 attributes
Objective: Single period return (0) vs i) multiple periods return (1) and ii) at different rates (1) 2 attributes	Objective: If switches to a higher value box (1), 0 otherwise 1 attribute	Objective: Risk-taking behaviour (three reward sets) no participation (1), a sure gain (2), low risk-return (3), high risk return (4) 3 attributes
✓ Score, min 0 and max 3	✓ Score, min 0 and max 1	✓ Score, min 3 and max 12
✓ Financial understanding score, min 3 and max 16		

Source: Authors' preparation.
Note: This table presents the process of measurements and calculation of financial understanding score. It is a cumulative measurement including three parameters. Each parameter has subjective and objective attributes. The scores for variables (at the attribute level) are reported in the parentheses.

3.3.2.2 Empirical strategy

The strategy in this study is to estimate each parameter of financial understanding separately and then the cumulative financial understanding. It uses three different models, i.e., logit model to estimate binary outcome variables, ii) the Ologit for the ordinal outcome variables, and iii) the OLS model for continuous risk score and financial understanding. The choice modelling approach generally uses a random utility maximization approach. A decision-maker chooses an option that maximizes the utility based on case-specific and alternative-specific variables (McFadden, 2001). Choice modelling in such a process observes the option chosen and the attributes of both the decision-maker and choice options. Thus, the approach allows the endogeneity of case variables, i.e., solar irrigation use. However, this may or may not explain the causality between a decision-maker's attributes and the chosen option. Solar irrigation use is not assumed to depend on the selected explanatory variables. Instead, the intention is to estimate choices on solar irrigation use, controlled for the selected covariates for farm and household characteristics. Neither do solar providers use these attributes to select users nor do I use them to match the solar and non-solar groups. In addition, financial understanding indicators are not used to select solar using farmers. The regression process uses the following linear predicted model of outcome variable y_i in each subjective and objective choice:

$$y_i = \alpha_0 + \alpha_1 T_i + \hat{\beta} X_i \qquad \text{Equation 3. 1}$$

Here, it estimates the probability of making a choice (i.e., the indicated variables, coded as 1 in each choice set described above). The choice takes place in terms of log odds as a linear combination of the selected explanatory variables. The probability of $y_i = 1|treatment_i, X_i$ ranges between 0 and 1 and the logit function is, $p_i =$. The expression, $1 - p_i = \frac{1}{1+ e^{(\alpha_0 + \alpha_1 T + \hat{\beta} X_i)}}$ is the probability of $y_i = 0|treatment_i, X_i$. The logit model is:

$$\ln\left(\frac{p_i}{1 - p_i}\right) = \alpha_0 + \alpha_1 T_i + \hat{\beta} X_i + \epsilon_i \qquad \text{Equation 3. 2}$$

Here, $\alpha_1 = \left(\frac{\partial p_i}{\partial T_i}\right)$ estimates the probability of the outcome variable taking value 1 if a farmer uses solar irrigation and ϵ_i is the random component. The results section reports the odds ratio and marginal effect for each choice. The odds ratio $\left(\frac{\hat{p}_i}{1-\hat{p}_i}\right)$ of the solar adoption in favour of i) forward-looking, ii) understanding ability, and iii) risk-taking behaviours are reported. This odds ratio gives a probability comparison of an outcome variable between solar and non-solar groups. The marginal effect shows the magnitude of the relationship between solar irrigation use and the predicted probability of each choice of the financial understanding parameters. Finally, margins are reported, i.e., average predicted probabilities of each choice response at specified values of the solar adoption, i.e., solar=1 and non-solar=0.

The ordered logit model estimates the ordinal forward-looking behaviour levels and risk-taking behaviour levels. In the ordered logit model, categories are assumed not to overlap and require a natural ordering (Greene and Hensher, 2010). In our design, both choices in each set (all sets are mutually exclusive) represent returns in single and multiple periods. Thus, the constructed categories are naturally ordered based on the stated choice counts.

The 4-order outcome variable, y_i is a function of the latent variable y_i^* and I observe y_i^* through the following mechanism:

$$\begin{aligned} y_i &= 1 \; if \;\; y_i^* \leq \mu_1, \\ &= 2 \; if \; \mu_1 < y_i^* \leq \mu_{2,} \\ &= 3 \; if \; \mu_2 < y_i^* \leq \mu_3, \\ &= 4 \;\; if \;\; y_i^* > \mu_3. \end{aligned}$$

Here, $\mu_1 < \mu_2 < \mu_3 < \mu_4$ is the estimated critical value and that shows the relationship between the observed and latent outcome variable compared to the critical value. We now define the following model for the latent outcome variable[9],

$$y_i^* = \alpha_0 + \alpha_1 T_i + \acute{\beta} X_i + \epsilon_i \qquad \text{Equation 3. 3}$$

The estimates of $E(y_i^*) = \alpha_0 + \alpha_1 T_i + \acute{\beta} X_i$ in the Ologit model calculate,

$$p_r(y_i = 1) = \frac{1}{1 + e^{(\alpha_0 + \alpha_1 T_i + \acute{\beta} X_i - \mu_1)}}$$

$$p_r(y_i = 2) = \frac{1}{1 + e^{(\alpha_0 + \alpha_1 T_i + \acute{\beta} X_i - \mu_2)}} - \frac{1}{1 + e^{(\alpha_0 + \alpha_1 T_i + \acute{\beta} X_i - \mu_1)}}$$

9 For choice sets J and K, we observe 3-level ordered risk-taking behaviour and accordingly use Ologit model with the estimated critical levels as, $\mu_1 < \mu_2 < \mu_3$. To avoid repetitions, we do not write the model in detail in this section.

$$p_r(y_i = 3) = \frac{1}{1 + e^{(\alpha_0 + \alpha_1 T_i + \acute{\beta} X_i - \mu_3)}} - \frac{1}{1 + e^{(\alpha_0 + \alpha_1 T_i + \acute{\beta} X_i - \mu_2)}}$$

$$p_r(y_i = 4) = 1 - \frac{1}{1 + e^{(\alpha_0 + \alpha_1 T_i + \acute{\beta} X_i - \mu_3)}}$$

Here, the sum of all predicted probabilities equals 1. Marginal effects and margins are reported for each level of ordered outcome variables. Observing the raw difference for each level between solar and non-solar groups is also possible. The Ologit model assumes that α_1 and $\acute{\beta}$ are the same in each category, i.e., it holds the proportional odds assumption. This implies that the model gives similar odds ratios across all categories of the outcome variable. Brant's test confirms if this assumption holds.

Finally, the following OLS model estimates the cumulative forward-looking score, risk score, and financial literacy score:

$$y_i = \alpha_0 + \alpha_1 T_i + \acute{\beta} X_i + \varepsilon_i \qquad \text{Equation 3. 4}$$

Here, α_1 estimates the change in the constructed continuous variable's score if a farmer uses solar irrigation. ε_i is an error term with a mean of 0 and a constant variance. In the models written above, both $treatment_i$ and X_i (a set of K covariates) are assumed to be independent of ε_i. The covariates are independent of solar adoption and $\acute{\beta}$ is a vector of K parameters and our inference object. In this regard, correlation coefficients are calculated to show if there is any perfect linear relationship between explanatory variables. The covariates include the farmer's age and education, total household land possession, asset possession, number of rooms if a house is made of brick/tin/timber, and irrigation pump capacity. The descriptive statistics include the measures of the selected explanatory and outcome variables for the full sample, solar, and non-solar user groups. The table reports the means and standard deviations for the scale variables and frequency percentage of 'yes' responses for the categorical variables. A sample *t*-test for each variable tests the difference in means between solar and non-solar user groups. The estimation of financial understanding is controlled for the experience of financial investment and a regional dummy variable (taking them as constants). In Bangladesh, the average solar irrigation plant or system number is 54 and the average capacity of systems is 1.02 MWp at the district level. That is why the high solar adoption area (variable value is 1 if high and 0 otherwise) is identified as the areas which have more than the average number of systems and plants' average capacity. Similarly, the low adoption areas are those that have less than 54 solar systems and the average capacity is below 1.02 MWp at the district level.

3.3.3 Descriptive statistics and sample balancing tests

Table 3.2 presents the sample baseline characteristics, the outcome variables, and the sample balance tests of the selected explanatory variables for both groups of farmers. As observed from the p-value of differences, solar and non-solar using farmers have similar age distributions, asset possessions, conditions of houses (i.e., materials of house and number of rooms in a house) and previous investment experiences. Groups differ in years of education, farming experience (at the 5% significance level), and irrigation pump capacity, and if perceived that the cultivation is sustainable (at the 1% significance level). This implies that solar adopters have higher education years and use larger-size pumps than non-adopters. However, the solar group has less farming experience than the non-solar group. Overall, less than 50% of the farmers choose the forward-looking option (choice sets A, B, and C). Less than 40% of the farmers choose the 'money later' (choice set D). Thus, less than 40% have an understanding of calculation and opportunity costs. More than 80% of the farmers choose a risky option at least once among choice sets G, H, I, J, and K.

Table 3. 2 Descriptive statistics and the balancing tests of sample characteristics.

Sl. No.	Variables	Full sample Mean/ frequency	Solar adopters Mean/ frequency	Non-solar adopters Mean/ frequency	*p*-value of difference
A.	Explanatory variables				
1	Farmer's age (years)	45.42	44.9	45.94	0.2666
2	Farmer's education (schooling years)	4.72	5.16	4.29	0.0183
3	If the house is made of brick/tin/timber (yes=1 and no=0)	83.50% (yes)	83.50% (yes)	83.50% (yes)	1.0000
4	Household rooms (number)	2.93	2.86	3	0.1537
5	Asset possession (number)	9.18	9.06	9.31	0.3865
6	Pump capacity (kwh)	10.01	13.07	6.95	0.0000
7	If perceives that cultivation is sustainable (yes=1 and no=0)	95.75% (yes)	99.25% (yes)	92.25% (yes)	0.0000
8	If have any past investment experience (yes=1 and no=0)	17.38% (yes)	17.50% (yes)	17.25% (yes)	0.9258
B.	Outcome variables				
9	Choice A: big ball (0) vs small balls (1)	45.13% (yes)	53.75% (yes)	36.50% (yes)	0.0000
10	Choice B: return in one day (0) vs return in 7 days (1)	38.25% (yes)	46.50% (yes)	30.00% (yes)	0.0000
11	Choice C: return in one day (0) vs return in 7 days at different rates (1)	42.13% (yes)	49.00% (yes)	35.25% (yes)	0.0000
12	Levels of financially forward-looking behaviour				0.0000 (chi-square value)
	Not forward-looking	41.50%	37.50%	45.50%	
	Low level	19.38%	15.50%	23.25%	
	Medium level	11.25%	7.25%	15.25%	
	High level	27.88%	39.75%	16.00%	
13	Choice D: money now (0) vs money later (1)	34.00% (yes)	37.25% (yes)	30.75% (yes)	0.0524
14	Choice E: switching to the solid box (no=0 and yes=1)	7.74% (yes)	9.56% (yes)	6.09% (yes)	0.1361
15	Choice F: switching to the transparent box (no=0 and yes=1)	85.98% (yes)	92.00% (yes)	78.51% (yes)	0.0014
16	Understanding calculation and opportunity cost by choosing money later or switching to a higher value box	39.12% (yes)	43.50% (yes)	34.75% (yes)	0.0112
17	Choice G: Big ball (0) vs possible broken box of small balls (1)	15.88% (yes)	16.75% (yes)	15.00% (yes)	0.4989
18	Choice H: Big ball (0) vs surely a broken box of small balls (1)	13.13% (yes)	15.00% (yes)	11.25% (yes)	0.1166
19	Choice I: Levels of risk-behaviour (scale of 4: no participation to high risk-return)	2.28	2.39	2.17	0.0003
20	Choice J: Levels of risk-behaviour (no participation, 50% chance for BDT100, 25% chance for BDT150)	2.07	2.13	2.00	0.0042
21	Choice K:Levels of risk-behaviour: (no participation, 75% chance for BDT50, 50% chance for BDT100)	2.19	2.26	2.12	0.0065
22	Risk score: min 3 and max 12	6.84	7.12	6.56	0.0001
23	Financial understanding score: min 3 and max 16	8.42	8.96	7.88	0.0000

Source: Authors' calculation.

Note: This table reports the descriptive statistics of the controlled/sample balancing variables (1-8) and the outcome variables (9-23). The *p*-value in the last column shows the significance test of the mean difference for each variable between solar and non-solar irrigation user farmers. Percentage frequencies of "yes" are reported for the discrete binary variables. For the ordinal variables, the chi-square test shows the category-wise variation strength (Sl No. 15). The visual representation of the selected explanatory variables is provided in Figure 3.3. A correlation table is also prepared (Figure 3.1) to check the multicollinearity between the selected explanatory variables.

if use solar irrigation								
-0.039	farmer's age							
0.083	-0.307	farmer's schooling years						
0.000	0.069	0.021	if house is brick/tin/timber built					
-0.050	0.076	0.168	0.165	household rooms				
-0.031	0.090	0.210	0.177	0.467	total household assets			
0.530	-0.083	0.076	-0.207	-0.022	-0.039	irrigation pump capacity		
0.174	-0.076	-0.009	-0.094	0.039	-0.003	0.199	if use any sustainable farming practice	
-0.000	-0.089	0.145	0.034	0.109	0.124	-0.004	0.031	if had previous investments

Figure 3. 1 The correlation table for the selected explanatory variables.

Source: Authors' preparation.
Note: This figure shows that there is no perfect collinearity between the selected explanatory variables. Two separate colours are used for positive (bluish grey) and negative (whitish) correlations between variables.

Regarding group-wise descriptive statistics, solar adopters seem more forward-looking and risk-takers and they possess better calculation ability than non-adopters. The computed forward-looking score and risk score are higher than the average values among solar users. Thus, solar adopters have a higher financial understanding score than non-adopters.

3.4 Results

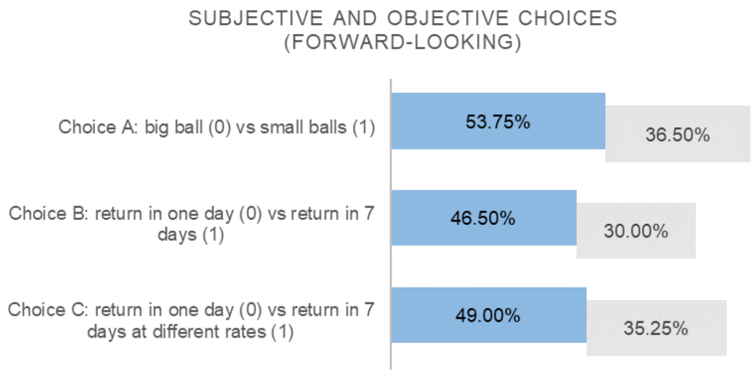
3.4.1 What impacts the financially forward-looking behaviour

Figure 3.2 presents the percentage distributions of the stated subjective and objective choices of financially forward-looking behaviour. The distributions between choices for all three sets are similar within the non-solar group. For the choice sets A, B, and C, the percentage distributions for non-solar irrigation user-farmers are higher for the big-ball box and a single-period return. The distributions are symmetric between two options in each choice set for solar users. Between choices of small balls and a big ball, and between one-day return and 7-day return, solar users have higher percentages than non-solar groups. After combining all the choices on a scale of 4, most solar users' behaviour is highly forward-looking, while non-solar users mostly fall in the not-forward-looking category.

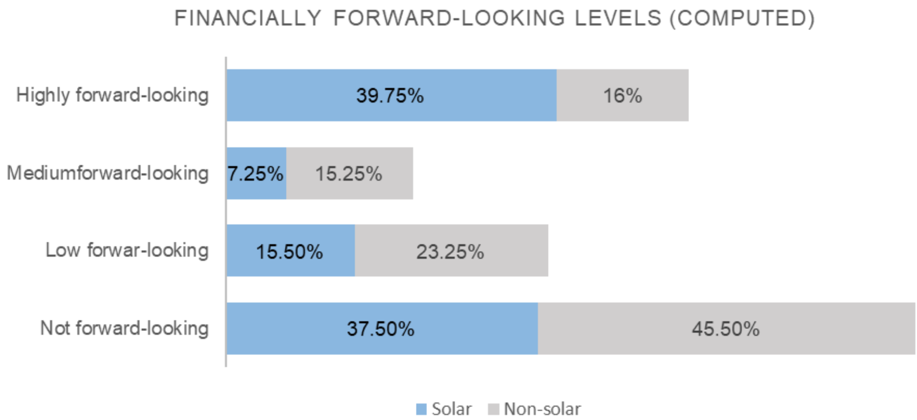
Table 3.3, Table 3.4, Table 3.5, Table 3.6, and Figure 3.3 present the predicted probability of the choices and forward-looking behaviour for being a solar irrigation user. Logit, OLS, and Ologit models' results suggest that solar irrigation use increases the probability of making choices of small balls, return in 7 days and return in 7 days at different rates (at the 1% significance level) and consequently solar users tend to be more financially forward-looking. In model 3.1.a, the odds of choosing small balls for solar users are 2.41 times as large as the same for non-adopters. Similarly, for solar adopters, the odds of choosing return in 7 days and 7 days at different rates are respectively 2.08 (model 3.2.a) and 1.95 times (model 3.3.a) as large as the same for non-adopters. Marginal effects show that being a solar user increases the probability of choosing small balls by 21.4 percentage points, returns in 7 days by 17.03 percentage points, and returns in 7 days at different rates by 16.12 percentage points. In choice C, probability reduces perhaps because of its relatively complex calculation. The impact strengths in subjective and objective choices are different. Solar irrigation use has a stronger impact on subjective choices than on objective choices. Regarding the feedback of stated choices, most solar users preferred small balls and 7-day returns perceiving- i) a larger return and ii) in multiple periods. For solar users, such a choice resembled a continued investment, while non-solar users identified it as a long-term investment. The existing literature provides similar findings. For example, Kim et al. (2023) demonstrated that forward-looking users opt for *lifetime* hunting licences. Non-solar farmers who chose a single period mentioned that periodic return is sometimes insignificant in multi-period investments. Solar users who chose returns in 7 days perceive that multiple periods give a higher return. They can spend and invest frugally for a longer period. Solar farmers also perceived that multi-period return is a sustainable choice and helps in income diversification. Non-solar users who chose a 7-day return gave similar reasons for receiving a higher return, yet they did not elaborate on that. This shows a lower cognitive ability of non-solar farmers. These reasons explain why the forward-looking behaviour level differs between adopter and non-adopter groups. Overall, farmers who choose one-day return in both groups, prefer fewer complications in calculations, and a substantial return that can serve one single purpose. The expense could be on loan repayment, consumption purposes, and even on investment. Such perception may come from individual traits and real-life scenarios. I did not observe loan access or amount in this study for which the estimated choices can be biased. The survey shows that only 14.89% of farmers received agricultural credits (Table 3.2). When I include the variable in the model, it does not have an impact on the stated choices and inclusion of this variable reduces the goodness of fit. It is possible because farmers often take consumption loans from their peers. Even if they get loans from institutions, they use the money for consumption purposes. Loan amount therefore could not influence the stated choices.

Heterogeneity and robustness

Solar users compared to non-solar users in high adoption areas are 2.85 times more likely to choose small balls, 2.83 times more likely to choose the 7-day return option, and 2.88 times more likely to choose 7-day return at various rates. The empirical results for the constructed financially forward-looking behaviour in model 3.4.a suggest that solar-use increases the forward-looking score by 0.53 points. Solar users' forward-looking score in highly adopted areas increases by 0.71 points. Solar use does not impact these choices in low adoption areas. This further suggests that the role of solar adoption intensity can induce residents' forward-looking behaviour collectively. Ologit model results show that solar adopters are less likely to be in the not-forward-looking category (-0.1814), while they are most likely to be highly forward-looking (by 14.99 percentage points). Solar irrigation does not have any impact on the low forward-looking category. Figure 3.3 shows that the predicted forward-looking behaviour exhibits a larger group-wise difference from medium to high levels. Regarding other farm characteristics, farmers who have brick/tin/timber-built houses are more likely to choose small balls and return in multiple periods, hence they tend to be more forward-looking (at the 1% significance level). A negative sign on the coefficient of a farmer's age implies that younger farmers are more likely to make choices of long-term options and higher return, i.e., small balls and return in multiple periods (at the 5% significance level). Small-size irrigation plant users are more likely to choose multiple balls, i.e., the subjective forward-looking option.



(3.2.a)



(3.2.b)

Figure 3. 2 Percentage distributions of outcome variables of financially forward-looking choices and levels for non-solar and solar group

Source: Authors' preparation.

Note: This figure presents the percentage distributions of the stated choices showing financially forward-looking behaviour for non-solar and solar groups separately. The first image 3.2.a respectively plots the binary choices between a box of one big ball and a box of small balls, between return in one day and return in 7 days, and between return in one day and return in 7 days at different rates. The second image 3.2.b shows the ordinal levels (a scale of 1-4): not forward-looking, and low, medium, and high levels of forward-looking behaviour. This variable is constructed by combining the first three binary choices.

Plant capacity has no impact on the choice-making controlled for network intensity and in objective forward-looking behaviour. That suggests, for a new technology switch, that it would be useful for providers to select cognitively forward-looking farmers even if it is a small project. Farmers' education level and better living conditions in low adoption areas show positive impacts on fractional returns. However, these variables do not have any significant effects in high adoption areas, indicating a robust effect of solar use in such cases. Young farmers in high adoption areas have a higher forward-looking score. Better housing condition increases the score for the full sample and with high and low adoption intensity. Farmers' education does not increase the additive forward-looking score, indicating less contribution of education on financial understanding in the study area.

Table 3. 3 The estimated probability of Choice A.

	Choice A: big ball (0) vs small balls (1)					
	Model 3.1.a Full sample		Model 3.1.b High adoption areas		Model 3.1.c Low adoption areas	
Variables	Odds ratio	Marginal effect	Odds ratio	Marginal effect	Odds ratio	Marginal effect
If a solar irrigation user	2.4097***	0.2142***	2.8547***	0.2534***	1.6947	0.1298
	(0.4343)	(0.0425)	(0.6340)	(0.0512)	0.6253	(0.0898)
Farmer's age	0.9883**	-0.0029**	0.9820**	-0.0044**	0.9924	-0.0019
	(0.0058)	(0.0015)	(0.0086)	(0.0021)	(0.0082)	(0.0020)
Farmer's education	1.0115	0.0028	1.0103	0.0025	1.0070	0.0017
	(0.0156)	(0.0038)	(0.0209)	(0.0051)	(0.0245)	(0.0060)
If the house is brick/tin/timber	1.4206*	0.0852*	1.5889*	0.1121*	1.1867	0.0419
	(0.2996)	(0.05)	(0.4192)	(0.0621)	(0.4872)	(0.0995)
Number of rooms	0.8930*	-0.0280*	0.9203	-0.0205	0.8621	-0.0367
	(0.0547)	(0.0152)	(0.0784)	(0.0210)	(0.0805)	(0.0231)
Asset possession	0.9925	-0.0019	1.0190	0.0046	0.9666	-0.0084
	(0.0213)	(0.0053)	(0.0305)	(0.0074)	(0.0304)	(0.0078)
Irrigation pump capacity	0.9657**	-0.0086**	0.9712	-0.0071	0.9881	-0.0030
	(.0171)	(0.0044)	(0.0212)	(0.0053)	(0.0358)	(0.0090)
Sample size	800		414		386	
Log-likelihood ratio	-529.67		-267.49		-259.01	
Prob > chi2 or F	0.0000		0.0000		0.0644	

Source: Authors' calculation.

Note: This table reports the results for the predicted probabilities of choice A, i.e., choice of small balls for the full sample, the sample in high, and the sample in low adoption areas respectively. The details of the results are discussed in Section 3.4.1 and the percentage distribution of the outcome variables by non-solar and solar groups is presented in Figure 3.4. In the logit models (Equation 3. 1) for binary choices, both odds ratios and marginal effects are reported. The estimated odds ratios for binary outcome variables are visualized for both solar and non-solar groups in Figure 3.5. The significant chi-square statistics in logit models say that the variable of interest, solar irrigation use has a significant impact on making the choice. Appendix A includes the sensitivity analyses of these models. The standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 3. 4 The estimated probability of Choice B.

	Choice B: return in one day (0) vs return in 7 days (1)					
	Model 3.2.a Full sample		Model 3.2.b High adoption areas		Model 3.2.c Low adoption areas	
Variables	Odds ratio	Marginal effect	Odds ratio	Marginal effect	Odds ratio	Marginal effect
If a solar irrigation user	2.0824***	0.1703***	2.8307***	0.2323***	1.2529	0.0538
	(0.3811)	(0.0416)	(0.6448)	(0.0486)	(0.4675)	(0.0889)
Farmer's age	0.9903	-0.0023	0.9876	-0.0028	0.9939	-0.0015
	(0.0060)	(0.0014)	(0.0089)	(0.0021)	(0.0084)	(0.0020)
Farmer's education	1.0120	0.0028	0.9978	-0.0005	1.0311	0.0073
	(0.0159)	(0.0037)	(0.0213)	(0.0049)	(0.0256)	(0.0059)
If the house is brick/tin/timber	2.1872***	0.1678***	1.5847*	0.1005*	7.1050***	0.3330***
	(0.4953)	(0.0431)	(0.4310)	(0.0566)	(4.4844)	(0.0600)
Number of rooms	0.9308	-0.0168	0.9478	-0.0122	0.9230	-0.0191
	(0.0586)	(0.0148)	(0.0836)	(0.0200)	(0.0866)	(0.0224)
Asset possession	0.9628*	-0.0089*	0.9904	-0.0022	0.9351**	-0.0160**
	(0.0216)	(0.0053)	(0.0311)	(0.0071)	(0.0305)	(0.0078)
Irrigation pump capacity	0.9925	-0.0018	0.9981	-0.0004	1.0147	0.0035
	(0.0178)	(0.0041)	(0.0224)	(0.0051)	(0.0379)	(0.0089)
Sample size	800		414		386	
Log-likelihood ratio	-509.76		-255.82		-247.26	
Prob > chi2 or F	0.0000		0.0001		0.0003	

Source: Authors' calculation.

Note: This table reports the results for the predicted probabilities of choice B, i.e., choice of 7-day return for the full sample, the sample in high, and the sample in low adoption areas respectively. The details of the results are discussed in Section 3.4.1 and the percentage distribution of the outcome variables by non-solar and solar groups is presented in Figure 3.4. In the logit models (Equation 3. 1) for binary choices, both odds ratios and marginal effects are reported. The estimated odds ratios for binary outcome variables are visualized for both solar and non-solar groups in Figure 3.5. The significant chi-square statistics in logit models say that the variable of interest, solar irrigation use has a significant impact on making the choice. Appendix A includes the sensitivity analyses of these models. The standard errors are in parentheses and *** p < 0.01, ** p < 0.05, * p < 0.10.

Table 3. 5 The estimated probability of Choice C.

	Choice C: return in one day (0) vs return in 7 days at different rates (1)					
	Model 3.3.a Full sample		Model 3.3.b High adoption areas		Model 3.3.c Low adoption areas	
Variables	Odds ratio	Marginal effect	Odds ratio	Marginal effect	Odds ratio	Marginal effect
If a solar irrigation user	1.9515***	0.1612***	2.8833***	0.2414***	1.2499	0.0555
	(0.3501)	(0.0425)	(0.6503)	(0.0491)	(0.4643)	(0.0922)
Farmer's age	0.9860**	-0.0034**	0.9849*	-0.0035*	0.9877	-0.0031
	(0.0058)	(0.0015)	(0.0088)	(0.0021)	(0.0082)	(0.0021)
Farmer's education	1.0173	0.0042	0.9983	-0.0004	1.0571**	0.0138**
	(0.0157)	(0.0038)	(0.0211)	(0.0049)	(0.0260)	(0.0061)
If the house is brick/tin/timber	1.7349***	0.1282***	1.3942	0.0753	2.3252**	0.1962**
	(0.3734)	(0.0472)	(0.3727)	(0.0588)	(1.0331)	(0.0921)
Number of rooms	0.9433	-0.0142	1.0079	0.0018	0.9024	-0.0256
	(0.0575)	(0.0148)	(0.0869)	(0.0200)	(0.0815)	(0.0225)
Asset possession	0.9792	-0.0051	0.9882	-0.0028	0.9667	-0.0084
	(0.0212)	(0.0053)	(0.0306)	(0.0072)	(0.0302)	(0.0078)
Irrigation pump capacity	0.9780	-0.0054	0.9940	-0.0014	0.9796	-0.0051
	(0.0172)	(0.0043)	(0.0221)	(0.0052)	(0.0361)	(0.0092)
Sample size	800		414		386	
Log-likelihood ratio	-526.62		-259.63		-257.59	
Prob > chi2 or F	0.0000		0.0001		0.0102	

Source: Authors' calculation.

Note: This table reports the results for the predicted probabilities of choice C, i.e., choice of 7-day return at different rates for the full sample, the sample in high, and the sample in low adoption areas respectively. The details of the results are discussed in Section 3.4.1 and the percentage distribution of the outcome variables by non-solar and solar groups is presented in Figure 3.4. In the logit models (Equation 3. 1) for binary choices, both odds ratios and marginal effects are reported. The estimated odds ratios for binary outcome variables are visualized for both solar and non-solar groups in Figure 3.5. The significant chi-square statistics in logit models say that the variable of interest, solar irrigation use has a significant impact on making the choice. Appendix A includes the sensitivity analyses of these models. The standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 3. 6 The estimated forward-looking score and levels.

	Forward-looking score			Forward-looking behaviour: not forward-looking	Forward-looking behaviour: low level	Forward-looking behaviour: medium level	Forward-looking behaviour: high level
	Model 3.4.a	Model 3.4.b	Model 3.4.c			Model 3.4.d	
Variables	Full Sample (Coefficient)	High adoption areas (Coefficient)	Low adoption areas (Coefficient)	Probability of outcome 1	Probability of outcome 2	Probability of outcome 3	Probability of outcome 4
If a solar irrigation user	0.5251*** (0.1018)	0.7108*** (0.1256)	0.2372 (0.2058)	-0.1814*** (0.0374)	0.0025 (0.0048)	0.029*** (0.0069)	0.1498*** (0.0315)
Farmer's age	-0.0082** (0.0036)	-0.0102* (0.0052)	-0.0061 (0.0052)	.0035*** (.0013)	-0.0001 (0.0001)	-0.0006** (0.0002)	-0.0028*** (0.0010)
Farmer's education	0.0093 (0.0092)	0.0011 (0.0121)	0.0224 (0.0147)	-0.0028 (0.0033)	0.0001 (0.0001)	0.0005 (0.0006)	0.0023 (0.0028)
If the house is brick/tin/timber	0.3706*** (0.1190)	0.2721* (0.1495)	0.5714*** (0.2018)	-0.1371*** (0.0473)	0.0115 (0.0078)	0.0249*** (0.0097)	0.1006*** (0.0311)
Number of rooms	-0.0552 (0.0336)	-0.0281 (0.0470)	-0.0755 (0.0502)	0.0185 (0.0129)	-0.0003 (0.0005)	-0.0030 (0.0022)	-0.0151 (0.0106)
Asset possession	-0.0146 (0.0123)	0.0003 (0.0169)	-0.0308* (0.0180)	0.0054 (0.0047)	-0.0001 (0.0001)	-0.0009 (0.0008)	-0.0044 (0.0038)
Irrigation pump capacity	-0.0139 (0.0095)	-0.0072 (0.0113)	-0.0051 (0.0204)	0.0061 (0.0037)	-0.0001 (0.0002)	-0.0010 (0.0006)	-0.0050 (0.0031)
Sample size	800	414	386			800	
Log-likelihood ratio						-1001.88	
Prob > chi2 or F	0.0000	0.0000	0.0003			0.0000	

Source: Authors' calculation.

Note: This table reports the results of different levels of forward-looking behaviour. The details of the results are discussed in Section 3.4.1. Four levels of forward-looking behaviour are predicted in ordered logit models (Equation 3. 3). The predicted levels of for-ward-looking behaviour are visualized for both solar and non-solar groups in Figure 3.5. The significant chi-square statistics of Ologit models say that the variable of interest, solar irrigation use has a significant impact on forward-looking behaviour levels. In the Brant test for the Ologit model, a significant test statistic shows that the assumption of parallel lines is violated. However, this assumption is violated for solar irrigation use only. For further specification, an unconstrained generalized Ologit model is run for the forward-looking behaviour levels where the chi-square statistic becomes insignificant (Prob > chi2 = 0.4027) (Appendix A). In the gOlogit model, the nature and significance of the effects of the explanatory variables remain the same as observed in the Ologit model results (Table 3.A.1). The standard errors are in parentheses, and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

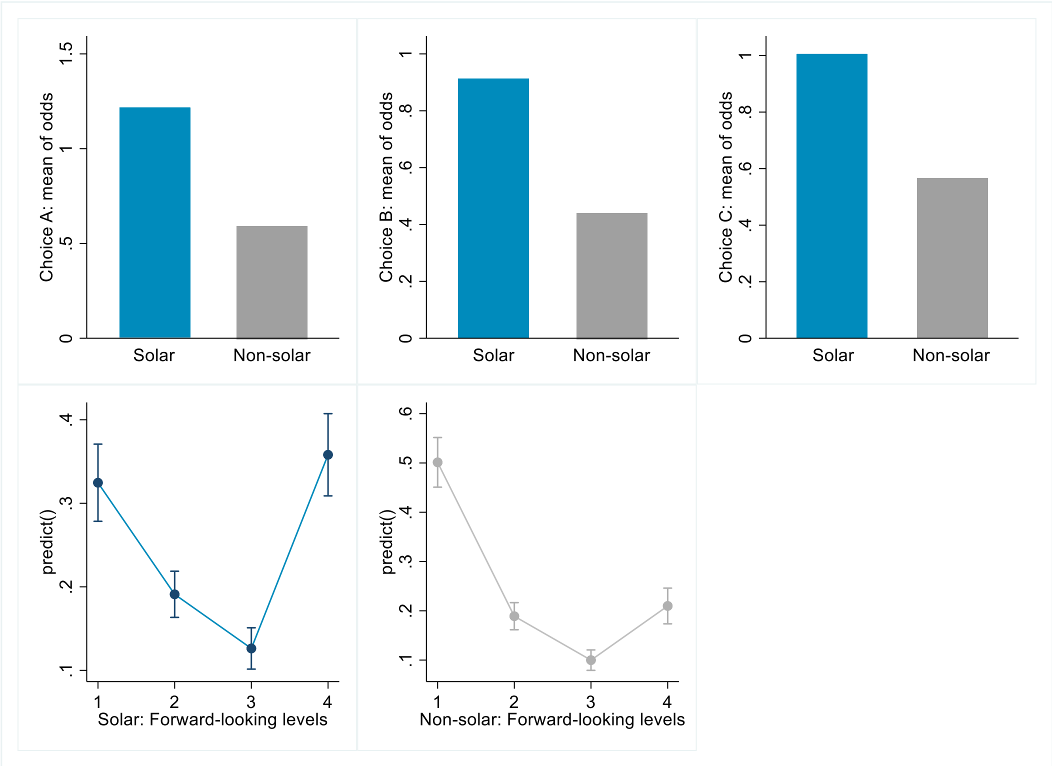
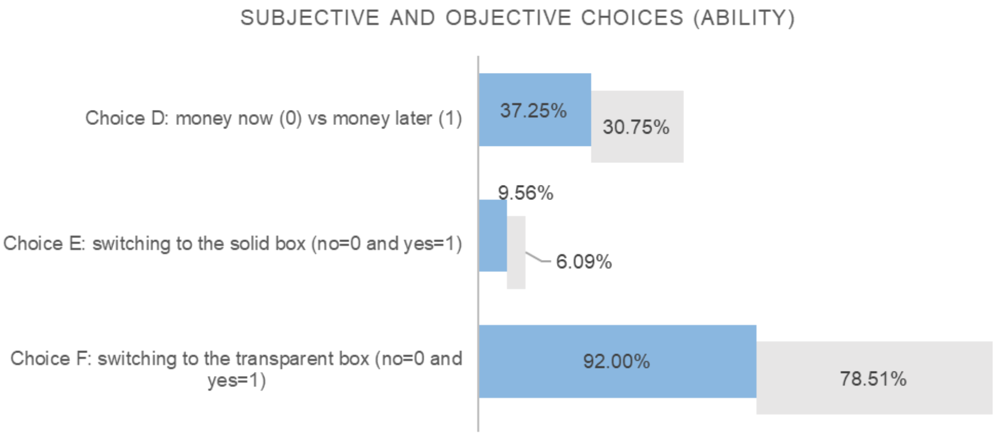


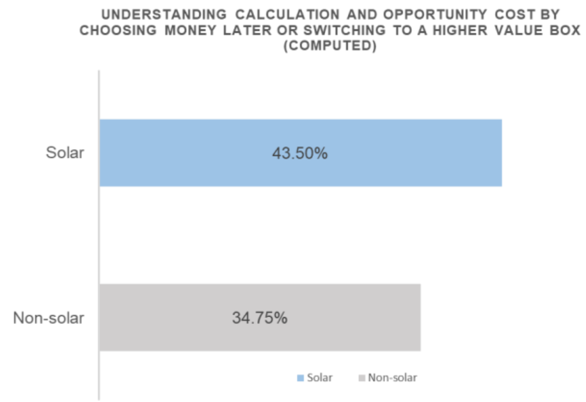
Figure 3. 3 Estimated financially forward-looking choices and levels for non-solar and solar groups.
Source: Authors' preparation.
Note: This figure presents the estimated logit and Ologit, regression results in models 3.1.a, 3.2.a, 3.3.a and 3.4.d for non-solar and solar groups. The first three plots in the upper panel show the means of odds ratios of three binary choices. In the lower panel, the probabilities of four levels of forward-looking behaviour are plotted for both groups.

3.4.2 What impacts the ability of understanding calculation and opportunity costs

Figure 3.4 presents the percentage distribution of the stated choices of understanding calculation and opportunity cost across solar adopter and non-adopter groups. In choice set D, though overall most farmers chose a transparent box against the solid one, a higher percentage of solar users compared to the non-solar users preferred the solid box or 'money later' option. It is possible because the solid box offer was unknown. A very low percentage of farmers who chose the transparent box switched to the solid box in the choice set E. Most farmers in both groups who chose the solid box initially switched their choice to the transparent box in the choice set F. This indicates that even if the ‘money later’ option could offer more, farmers preferred the visible option (i.e., ‘money now’) in choice E. Similarly when the visible option has a higher value in choice F, farmers switched choices. It appears that if the return is known or certain, it affects farmers’ understanding of calculation and opportunity costs.



(3.4.a)



(3.4.b)

Figure 3. 4 Percentage distributions of the outcome variables of the understanding of calculation and opportunity cost for non-solar and solar groups.

Source: Authors’ preparation.
Note: This figure presents the percentage distributions of the stated choices showing the understanding of calculation and opportunity cost for non-solar and solar groups separately. The first image 3.4.a plot the distribution of binary choices between a transparent box of one big ball and a solid box of small balls representing money now and money later choices respectively. It also shows the choices if farmers wish to switch boxes, to either the transparent or the solid boxes. The second choice set is given to farmers who selected the transparent box in the first set in this experimental stage and the third set is offered to farmers who opted for the solid box. Finally, the ability variable is constructed by combining three choices in image 3.4.b.

To observe the correlations between irrigation energy use and the understanding of calculation and opportunity cost, the binary stated choices D, E, and F are estimated in models 3.5-3.7. The results show that solar irrigation use has a significant impact on the stated choices and farmers' understanding. The odds of the 'money later' option for solar adopters is 1.67 times as large as the same for non-adopters (model 3.5.a). The odds of switching to a higher valued box for solar adopters are respectively 2.64 (model 3.6.a) and 2.82 (model 3.7.a) times as large as the same for non-adopters in model 3.6.a and model 3.7.a. The difference in the odds ratios in models 3.6.a and 3.7.a bear significant implications. It suggests that solar users who prefer the money later option tend to have a higher understanding. Similarly, when the constructed ability variable is estimated on being a solar user, I observe that solar users are 1.92 times abler than non-adopters. The marginal effect explains that being a solar user increases the understanding by 15.39 percentage points. When surveyors asked the reasons for the stated choice of a transparent box in all three choice sets, both solar and non-solar user farmers emphasized the visibility of the choices. Farmers particularly expressed that calculation is easy when a box's offer is visible. This reflects their preference for certainty in return calculation. It is also possible that it is their dislike for any unknown matter. Solar users explained that the invisibility of the box symbolizes uncertainty and risk. The invisible box does not seem to be a materialistic choice and they may practice accordingly in their daily life. However, such practices are difficult to observe and less likely to be consistent. Solar users stated their preference for current consumption while choosing the transparent box. Non-solar users did not choose the unknown box even if they could perceive a higher offer, because they prefer awareness of loss to an unknown gain. They related such a choice to their actual cultivation practice. Non-solar farmers who chose 'money later' (the solid box), stated that the solid box offer is intriguing for them. However, solar farmers in this category are more perceptive and calculative about their choices. They demonstrated that the solid box or 'money later' option may sound like a risky option (as it is unknown), yet they prefer risky and a higher return. They calculated the possible total value of the solid box during the survey, assuming that there are at least five balls in the solid box. This indicates that solar users have a higher cognitive ability of the choices, which also reflected their optimism about the choices they made. For non-solar farmers who chose the solid unknown box, it is a mere spontaneous choice without understanding the offer features.

Heterogeneity and robustness

Solar users in the high adoption areas are more likely to choose- i) the 'money later' option (2.38 times higher), ii) switching to the solid box (6.24 times higher) and iii) switching to the transparent box (3.65 times higher). Similarly, solar users' ability to understand calculation and opportunity costs increases with solar adoption intensity (Table 3.9). Solar use increases the probability of such ability by 24.35 percentage points (odds ratio is 2.83) in the high adoption areas (15.39 percentage points for the full sample). Regarding farm characteristics, perceiving their cultivation practice as sustainable has a strong negative impact on the stated choices and the understanding (at the 1% significance level). This finding is important because most farmers in this experiment chose the money now over the money later option and switched to a higher value box only when it is visible. It suggests their subjective perception of sustainable agriculture does not objectively explain their choices, calculation ability, and understanding of opportunity cost. Similar to the forward-looking behaviour, money later choice and calculation ability are higher for younger farmers and if farmers' house is made of brick/tin/timber (at the 10% significance level). House condition in low adoption areas has a positive impact on the 'money later' choice, and relatedly the ability variable. Farmers who perceive their cultivation practice as sustainable in the high adoption areas are less likely to choose the 'money later' option and they have less calculation ability. Ability is also low among farmers in the low adoption areas perceiving their practice as sustainable. This suggests that farmers' perception of sustainability does not necessarily improve calculation ability and solar network intensity does not change the scenario.

Table 3. 7 The estimated probability of Choice D.

	Choice D: money now (0) vs money later (1)					
	Model 3.5.a Full sample		Model 3.5.b High adoption areas		Model 3.5.c Low adoption areas	
Variables	Odds ratio	Marginal effect	Odds ratio	Marginal effect	Odds ratio	Marginal effect
If a solar irrigation user	1.6753** (0.3156)	0.1146*** (0.0414)	2.3841*** (0.5432)	0.1962*** (0.0498)	1.1645 (0.4466)	0.0324 (0.0816)
Farmer's age	0.9884* (0.0060)	-0.0025* (0.0013)	0.9860 (0.0087)	-0.0032 (0.0020)	0.9882 (0.0087)	-0.0025 (0.0019)
Farmer's education	0.9999 (0.0153)	-0.0001 (0.0034)	0.9832 (0.0203)	-0.0039 (0.0047)	1.0071 (0.0251)	0.0015 (0.0053)
If the house is brick/tin/timber	1.4682* (0.3264)	0.0816* (0.0447)	1.5154 (0.3995)	0.0918 (0.0559)	3.8545** (2.4163)	0.2159*** (0.0666)
Irrigation pump capacity	0.9706 (0.0180)	-0.0066 (0.0041)	0.9988 (0.0223)	-0.0003 (0.0051)	0.9539 (0.0376)	-0.0101 (0.0084)
If use any sustainable on-farm activity	0.4628** (0.1690)	-0.1853** (0.0907)	0.2870** (0.1561)	-0.3023** (0.1244)	0.6529 (0.3288)	-0.0967 (0.1202)
Sample size	800		414		386	
Log-likelihood ratio	-502.95		-259.55		-234.53	
Prob > chi2 or F	0.0031		0.0008		0.0505	

Source: Authors' calculation.

Note: This table reports the logit (Equation 3. 1) regression results of the probability of choosing the money later option for the full sample, and in high, and low adoption areas. The details of the results and interpretation are discussed in Section 3.4.2. A different set of explanatory variables are used in model specifications for its fit. The percentage distributions of the outcome variables are presented in Figure 3.4. The odds ratios are visualized for non-solar and solar groups in Figure 3.5. Finally, the standard errors are in parentheses and *** p < 0.01, ** p < 0.05, * p < 0.10.

Table 3. 8 The estimate probabilities of Choice E and Choice F.

	Choice E: switching to the solid box (no=0 and yes=1)				Choice F: switching to the transparent box (no=0 and yes=1)			
	Model 3.6.a Full sample		Model 3.6.b High adoption areas		Model 3.7.a Full sample		Model 3.7.b High adoption areas	
Variables	Odds ratio	Marginal effect	Odds ratio	Marginal effect	Odds ratio	Marginal effect	Odds ratio	Marginal effect
If a solar irrigation user	2.6444** (1.1509)	0.0662** (.0298)	6.2375*** (4.5181)	0.0917** (0.0356)	2.8210** (1.2623)	0.1192** (0.0526)	3.6462** (1.992)	0.1331** (0.0593)
Farmer's age	0.9971 (0.0130)	-0.0001 (0.0008)	0.9960 (0.0222)	-0.0002 (0.0009)	1.0054 (0.01485)	0.0005 (0.0016)	1.0156 (0.0213)	0.0013 (0.0018)
Farmer's education	1.0247 (0.0335)	0.0015 (0.0021)	1.0465 (0.0543)	0.0019 (0.0021)	1.0339 (0.0401)	0.0036 (0.0041)	1.0018 (0.0501)	0. .0002 (.0044)
Irrigation pump capacity	0.9424 (0.0419)	-0.0038 (0.0028)	0.9528 (0.0682)	-0.0020 (0.0029)	1.0254 (0.0433)	0.0027 (0.0045)	--	--
If use any sustainable on-farm activity	0.2317** (0.1484)	-0.1695 (0.1114)	0.1915 (0.2439)	-0.1418 (0.1801)	0.4541 (0.3609)	-0.0663 (0.0499)	--	--
Sample size	530		265		270		150	
Log-likelihood ratio	-139.15		-55.28		-103.70		-49.76	
Prob > chi2 or F	0.0671		0.0680		0.0310		0.0896	

Source: Authors' calculation.

Note: This table reports the logit (Equation 3. 1) regression results for the probabilities of switching to the solid and transparent boxes respectively to observe the understanding of calculation and opportunity costs. The details of the results and interpretation are discussed in Section 3.4.2. A different set of explanatory variables are used in model specifications for its fit. There are very negligible number of solar observations in this category in the low adoption areas, hence the model is not estimated. The percentage distribution of the outcome variables is presented in Figure 3.4. The odds ratios are visualized for non-solar and solar groups in Figure 3.5. Finally, the standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 3. 9 Estimated probability of understanding calculation and opportunity costs.

	Understanding calculation and opportunity cost by choosing money later or by switching to a higher value box (no=0 and yes=1)					
	Model 3.8.a Full sample		Model 3.8.b High adoption areas		Model 3.8.c Low adoption areas	
Variables	Odds ratio	Marginal effect	Odds ratio	Marginal effect	Odds ratio	Marginal effect
If a solar irrigation user	1.9227*** (0.3539)	0.1539*** (0.0425)	2.8268*** (0.6357)	0.2435*** (0.0503)	1.3112 (0.4870)	0.0633 (0.0866)
Farmer's age	0.9891* (0.0058)	-0.0025* (0.0014)	0.9863 (0.0086)	-0.0033 (0.0021)	0.9896 (0.0083)	-0.0025 (0.0020)
Farmer's education	1.0067 (0.0150)	0.0015 (0.0035)	0.9934 (0.0202)	-0.0016 (0.0049)	1.0151 (0.0242)	0.0035 (0.0056)
If the house is brick/tin/timber	1.3547 (0.2878)	0.0701* (0.0475)	1.3937 (0.3595)	0.0778 (0.0589)	2.6423* (1.3522)	0.1951** (0.0826)
Irrigation pump capacity	0.9636* (0.0175)	-0.0087* (0.0043)	0.9941 (0.0220)	-0.0014 (0.0053)	0.9469 (0.0358)	-0.0128 (0.0088)
If use any sustainable on-farm activity	0.3418*** (0.1278)	- 0.2620*** (0.0864)	0.2464** (0.1368)	-0.3329** (0.1138)	0.4182* (0.2138)	-0.2138* (0.1244)
Sample size	800		414		386	
Log-likelihood ratio	-521.16		-263.95		-249.01	
Prob > chi2	0.0001		0.0000		0.0298	

Source: Authors' calculation.

Note: This table reports the logit (Equation 3. 1) regression results for the constructed ability variable, i.e., understanding of calculation and opportunity costs if either choose money later or switch to a higher valued box for the full sample and controlling for solar network intensity. The details of the results and interpretation are discussed in Section 3.4.2. The odds ratios are visualized for non-solar and solar groups in Figure 3.5. Finally, the standard errors are in parentheses and *** p < 0.01, ** p < 0.05, * p < 0.10.

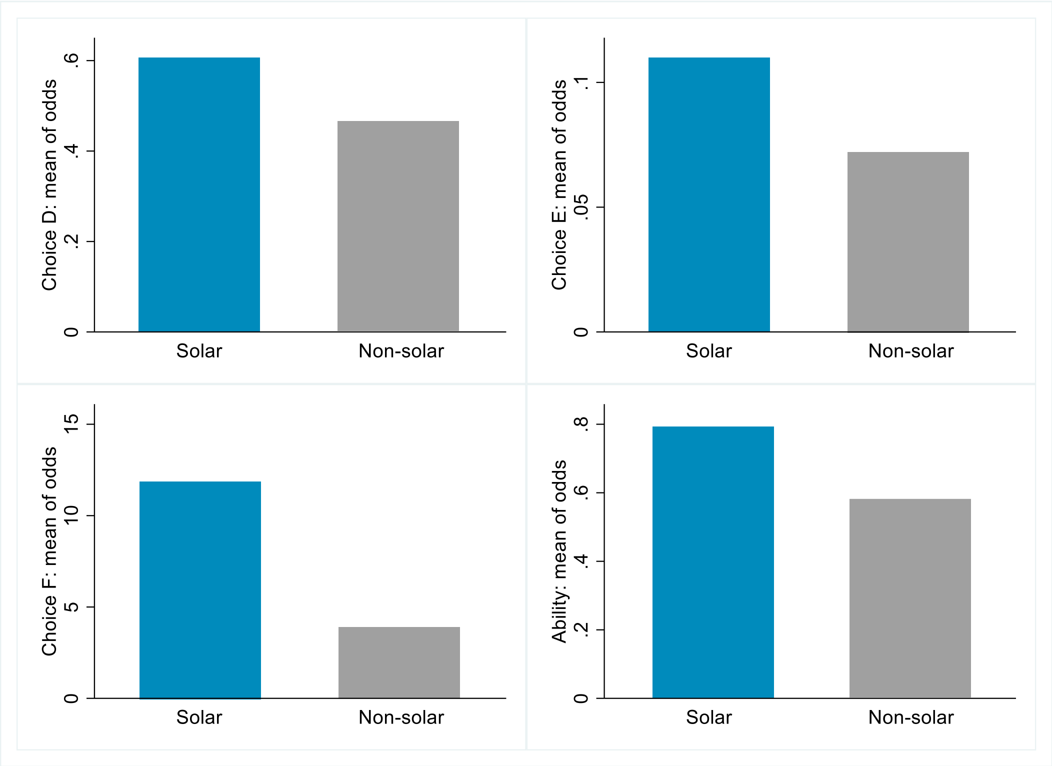


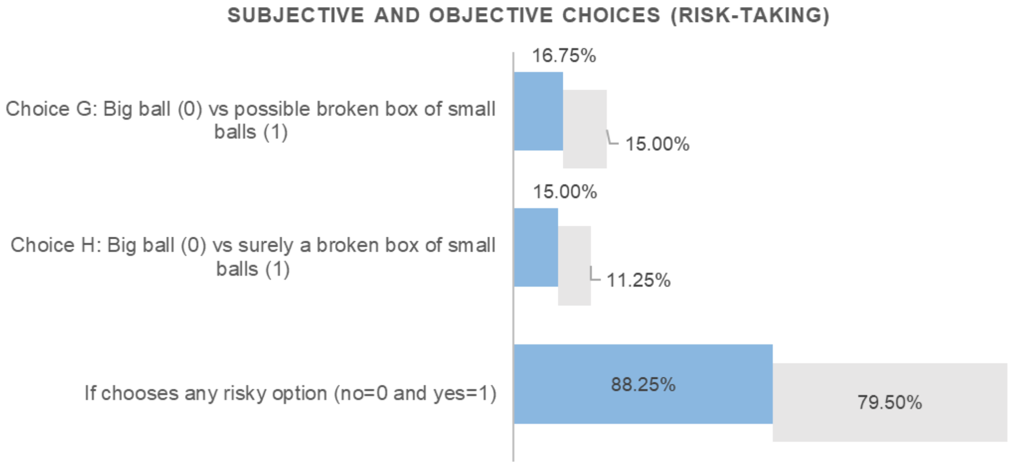
Figure 3. 5 Estimated understanding of calculation and opportunity cost for solar and non-solar groups.

Source: Authors' preparation.
Note: This figure presents the estimated logit, regression results in various models presented in Table 3.7, Table 3.8 and Table 3.9 for non-solar and solar groups (full sample). All graphs plot the means of odds ratios of logit models for non-solar and solar groups.

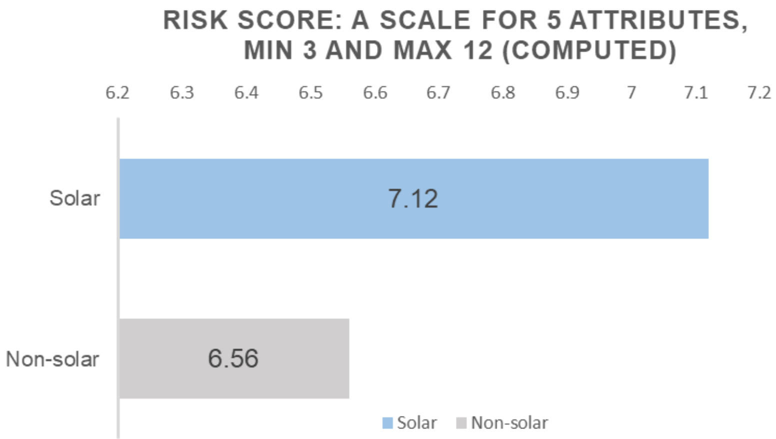
3.4.3 What affects risk perception and risk-taking behaviour

Figure 3.6 shows that in the subjective risk perception choice sets G and H, most farmers in both groups did not prefer the box (possibly broken or surely broken) of small balls. However, the pattern of choice changed across groups in lottery rewards games, i.e., in the objective part. Thus, it reflects that risk-taking behaviour differs between subjective and objective designs. In the first lottery game in the choice set I, most farmers chose the option of a sure gain in the full sample. Between groups, I observe that a higher percentage of solar users chose the high-risk-return reward than non-adopters did. In choices J and K, the percentage distribution indicate their higher preferences for high-risk-return options even if there is no surety of gain. The behaviour toward no participation changed when it removed the sure gain option from the rewards. Most farmers preferred risk-associated rewards to no participation. This suggests that risk-taking behaviour levels change with reward features. After combining all choice sets, the binary choice for risk perception and risk-taking behaviour and risk score shows similar patterns for both groups.

To examine the risk perception and risk-taking behaviour levels as impacted by the type of irrigation energy use, I estimate the stated choices in models 3.9-3.13 (Table 3.10, Table 3.11, and Table 3.12). The odds of choosing a possible broken box of small balls for solar farmers are 1.85 times than that for non-adopters. The reported marginal effect shows that the probability of choosing the possible broken box increases by 7.7 percentage points if it is a solar user. The magnitude of the probability of making a similar choice for a solar user increases even when the box is surely broken (by 10 percentage points).



(3.6.a)



(3.6.b)

Figure 3. 6 Percentage distributions of the outcome variables of risk perception and risk-taking behaviour levels for non-solar and solar groups.

Source: Authors' preparation.
Note: This figure presents the percentage distributions of the stated choices showing subjective risk perception and objective risk-taking behaviour levels for non-solar and solar groups separately. The first graph (3.7.a) plots the distributions of binary choices between a box of one big ball and a possible broken box of small balls and then a big ball box and surely a broken box of small balls. The binary choice distribution for choosing risky option(s) for both groups is plotted in this graph. The second image 3.7.b plots the distribution of the risk score for the two groups. This variable is constructed by adding all the subjective and objective risk perception choices and behaviour levels, i.e. G, H, I, J, and K.

The Ologit model's results show that the probability of no participation in the first and second lottery questions reduces for solar users. When rewards changed with a different return-risk level, solar use had no impact on 'no participation'. Solar users are more likely to participate in lottery games or anything deemed risky at any level. A similar impact is found for a sure gain reward, i.e., it reduces in Choice I, and in two other choices, solar use did not impact ‘a sure gain’ pick. Solar users tend to choose either low (4.21 percentage points) or high (3.55 percentage points) risk-return options in Choice I (Model 3.11). In Choice J, solar irrigation use increases risky choice-making (Model 3.12). Solar use increases the probability of choosing the high-risk-return option by 5.16 percentage points in model 3.12. This finding also implies that solar users are high-risk takers even if they do not sense a sure gain. After changing the reward features in Choice K, solar use is no longer impactful. There is no energy-oriented design effect after removing ‘a sure gain’. However, other controlled variables have differential impacts in Choices I, J, and K. Asset amounts are largely variable across risk-return preferences. Solar users with investment experience are high-risk takers. If these users understand reward features, high-risk preference increases (the marginal effects are 7 percentage points in Choice I and 15 percentage points in Choice K). Another notable aspect is that solar users with previous investment experiences made a stronger objective perception. Their subjective perception is not significant. These findings suggest that solar irrigation use has a stronger impact on subjective choices than on objective choices in the case of risk behaviour. When farmers mentioned the reasons for the stated choices, their personality traits and perception of lottery games dominated their choice behaviour. For instance, overall, farmers who expressed particular dislikes for lottery games chose ‘no participation’. Non-solar farmers particularly showed no interest in participation in a lottery game for religious reasons as they mentioned during the experiment. Farmers in both groups preferred a risky option because of a higher return that could serve a purpose.

Heterogeneity and robustness

The objective risk-taking behaviour varies considerably with the solar adoption network level. Solar users in the high adoption areas are more likely (2.29 times higher than non-solar users) to choose a box containing small balls while the box may be broken (Table 3.10). However, solar use does not show variations in pattern (both sign and significance) between high and low adoption areas when a possible broken box option is given (Table 3.11). This finding suggests that solar adoption intensity may not influence risk-taking behaviour. Households' asset possession and irrigation pump capacity have negative impacts on subjective risk perception in choices G and H.

Table 3. 10 The estimated probability of choice G.

	Choice G: Big ball (0) vs a possible broken box of small balls (1)					
	Model 3.9.a Full sample		Model 3.9.b High adoption areas		Model 3.9.c Low adoption areas	
Variables	Odds ratio	Marginal effects	Odds ratio	Marginal effects	Odds ratio	Marginal effects
If a solar irrigation user	1.8591** (0.4919)	0.0777** (0.0328)	2.2976*** (0.7110)	0.1138*** (0.0412)	1.4521 (0.7409)	0.0374 (0.0513)
Farmer's age	1.0019 (0.0078)	0.0002 (0.0009)	1.0053 (0.0107)	0.0007 (0.0015)	0.9942 (0.0120)	-0.0006 (0.0012)
Farmer's education	0.9981 (0.0211)	-0.0002 (0.0026)	0.9801 (0.0264)	-0.0027 (0.0037)	1.0034 (0.0370)	0.0003 (0.0037)
If the house is brick/tin/timber	1.8801** (0.6019)	0.0679** (0.0290)	2.0639** (0.7470)	0.0877** (0.0380)	5.2646 (5.4692)	0.0987*** (0.0321)
Asset possession	0.9189*** (0.0264)	-0.0105*** (0.0035)	0.9279** (0.0352)	-0.0102** (0.0051)	0.9098** (0.0411)	-0.0094** (0.0044)
Irrigation pump capacity	0.9296** (0.0256)	-0.0091*** (0.0034)	0.9627 (0.0298)	-0.0052 (0.0042)	0.8950* (0.0522)	-0.0111* (0.0057)
If have any past investment experience*being a solar user	0.6631 (0.2705)	-0.0454 (0.0395)	0.9167 (0.4295)	-0.0116 (0.0609)	0.2415 (0.2541)	-0.0924** (0.0392)
Sample size	800		414		386	
Log-likelihood ratio	-337.15		-185.15		-144.03	
Prob > chi2	0.0005		0.0102		0.0041	

Source: Authors' calculation.

Note: This table reports the logit (Equation 3. 1) regression results of the estimated choice of a possible broken box containing small balls. The details of the results are discussed in Section 3.4.3. The percentage distribution of the outcome variables by non-solar and solar groups is presented in Figure 3.6. The estimated odds ratios for binary outcome variables are visualized for both solar and non-solar groups in Figure 3.7. The significant chi-square statistics say that the variable of interest, solar irrigation use has a significant impact on making this choice. Finally, the standard errors are in parentheses and *** p < 0.01, ** p < 0.05, * p < 0.10.

Farmers even with limited assets and using a smaller size pump tend to make risky choices. These results are robust to a cumulated risk score (an additive score of subjective and objective responses). The linear prediction of the risk score shows that solar use increases the cumulative risk score (the coefficient size is 0.4946). The risk score is similar for users in high and low adoption areas. Investment experience increases and asset possession reduces this score. However, these variables do not have any impact on the risk-taking score of users in low adoption areas.

Table 3. 11 The estimated probability of Choice H.

	Choice H: Big ball (0) vs surely a broken box of small balls (1)					
	Model 3.10.a Full sample		Model 3.10.b High adoption areas		3.10.c Low adoption areas	
Variables	Odds ratio	Marginal effects	Odds ratio	Marginal effects	Odds ratio	Marginal effects
If a solar irrigation user	2.5681*** (0.7550)	0.1006*** (0.0307)	2.6001*** (0.9392)	0.1037*** (0.0377)	2.8170** (1.4234)	0.1001** (0.0503)
Farmer's age	0.9970 (0.0084)	-0.0003 (0.0009)	1.0040 (0.0120)	0.0004 (0.0013)	0.9880 (0.0124)	-0.0011 (0.0012)
Farmer's education	0.9854 (0.0226)	-0.0015 (0.0024)	0.9814 (0.0294)	-0.0020 (0.0032)	0.9833 (0.0377)	-0.0016 (0.0036)
If the house is brick/tin/timber	1.5491 (0.5179)	0.0412* (0.0278)	1.3830 (0.5313)	0.0328 (0.0364)	4.2932 (4.4628)	0.0862 (0.0343)
Asset possession	0.9448* (0.0287)	-0.0059* (0.0031)	0.9578 (0.0393)	-0.0046 (0.0044)	0.9366 (0.0431)	-0.0062 (0.0043)
Irrigation pump capacity	0.9100*** (0.0284)	- 0.0099*** (0.0031)	0.9414 (0.0349)	-0.0065* (0.0039)	0.8712** (0.0502)	-0.0130 (0.0053)
If have any past investment experience*being a solar user	0.7623 (0.3135)	-0.0262 (0.0363)	1.2808 (0.6080)	0.0287 (0.0593)	0.1999 (0.2101)	-0.0935 (0.0327)
Sample size	800		414		386	
Log-likelihood ratio	-300.02		-157.60		-137.65	
Prob > chi2	0.0026		0.0741		0.0100	

Source: Authors' calculation.

Note: This table reports the logit (Equation 3. 1) regression results of the estimated choice for a surely broken box containing small balls. The details of the results are discussed in Section 3.4.3. The percentage distribution of the outcome variables by non-solar and solar groups is presented in Figure 3.6. The estimated odds ratios for binary outcome variables are visualized for both solar and non-solar groups in Figure 3.7. The significant chi-square statistics in logit models say that the variable of interest, solar irrigation use has a significant impact on making this choice. Finally, the standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 3. 12 The predicted levels of risk-taking behaviours.

	Model 3.11				Model 3.12			Model 3.13		
	Risk-taking behaviour: no participation	Risk-taking behaviour: a sure gain	Risk-taking behaviour: low risk and return	Risk-taking behaviour: high risk and return	Risk-taking behaviour: no participation	Risk-taking behaviour: low risk and return	Risk-taking behaviour: high risk and return	Risk-taking behaviour: no participation	Risk-taking behaviour: low risk and return	Risk-taking behaviour: high risk and return
Variables	Probability of outcome 1	Probability of outcome 2	Probability of outcome 3	Probability of outcome 4	Probability of outcome 1	Probability of outcome 2	Probability of outcome 3	Probability of outcome 1	Probability of outcome 2	Probability of outcome 3
If a solar irrigation user	-.00410** (0.0184)	-0.0366** (0.0169)	0.0421** (0.0189)	0.0355** (0.0160)	-0.0410* (0.0248)	-0.0105 (0.0072)	0.0516* (0.0311)	-0.0314 (0.0234)	-0.0195 (0.0146)	0.0509 (0.0378)
Farmer's age	-0.0004 (0.0006)	-0.0004 (0.0005)	0.0004 (0.0006)	0.0003 (0.0005)	-.00003 (0.0008)	-0.0001 (0.0002)	0.0004 (0.0010)	-0.0007 (0.0007)	-0.0004 (0.0005)	0.0012 (0.0012)
Farmer's education	0.0020 (0.0015)	0.0018 (0.0014)	-0.0021 (0.0016)	-0.0017 (0.0013)	0.0029 (0.0021)	0.0007 (0.0006)	-0.0036 (0.0027)	0.0004 (0.0020)	-0.0002 (0.0012)	0.0007 (0.0033)
If the house is brick/tin/timber	0.0075 (0.0199)	0.0071 (0.0201)	-0.0079 (0.0214)	-0.0067 (0.0185)	-0.0261 (0.0302)	-0.0046 (0.0039)	0.0307 (0.0334)	0.0064 (0.0261)	0.0041 (0.0174)	-0,0106 (0.0436)
Asset possession	0.0005 (0.0020)	0.0005 (0.0018)	-0.0005 (0.0021)	-0.0004 (0.0017)	0.0053** (0.0027)	0.0013 (0.0008)	-0.0067** (0.0034)	0.0064** (0.0026)	0.0040** (0.0017)	-0.0105** (0.0042)
Irrigation pump capacity	-0.0015 (0.0016)	-0.0013 (0.0015)	0.0015 (0.0017)	0.0013 (0.0014)	-0.0029 (0.0023)	-0.0007 (0.0006)	0.0037 (0.0028)	-0.0016 (0.0021)	-0.0010 (0.0013)	0.0026 (0.0035)
If have any past investment experience*being a solar user	-0.0561*** (0.0180)	-0.0843** (0.0403)	0.0687*** (0.0252)	0.0717** (0.0330)	-0.0132 (0.0343)	-0.0041 (0.0127)	0.0173 (0.0469)	-0.0762*** (0.0252)	-0.0768** (0.0373)	0.1531** (0.0617)
Log-likelihood ratio	-902.5865				-776.0871			-818.5565		
Prob > chi2	0.0005				0.0154			0.0031		
Brant test (Prob > chi2)	0.011				0.000			0.061		

Source: Authors' calculation.

Note: This table reports the Ologit (Equation 3. 3) results of the estimated choices to identify risk perception and risk-taking behaviour levels. The details of the results are discussed in Section 3.4.3. Multiple levels of risk-taking behaviour are predicted in ordered logit models. The predicted levels of ordinal risk-taking behaviour are visualized for both solar and non-solar groups in Figure 3.7. The significant chi-square statistics in Ologit models say that the variable of interest, solar irrigation use has a significant impact on making each choice and risk-taking behaviour levels. In the Brant test for the Ologit model, a significant test statistic shows that the assumption of parallel lines is violated. However, this assumption is violated for solar irrigation use only. For further specification, an unconstrained generalized Ologit model is estimated for different risk-taking behaviours. In gOlogit model, the nature and significance of the effects of the explanatory variables remain the same as observed in the Ologit model results. Finally, the standard errors are in parentheses and *** p < 0.01, ** p < 0.05, * p < 0.10.

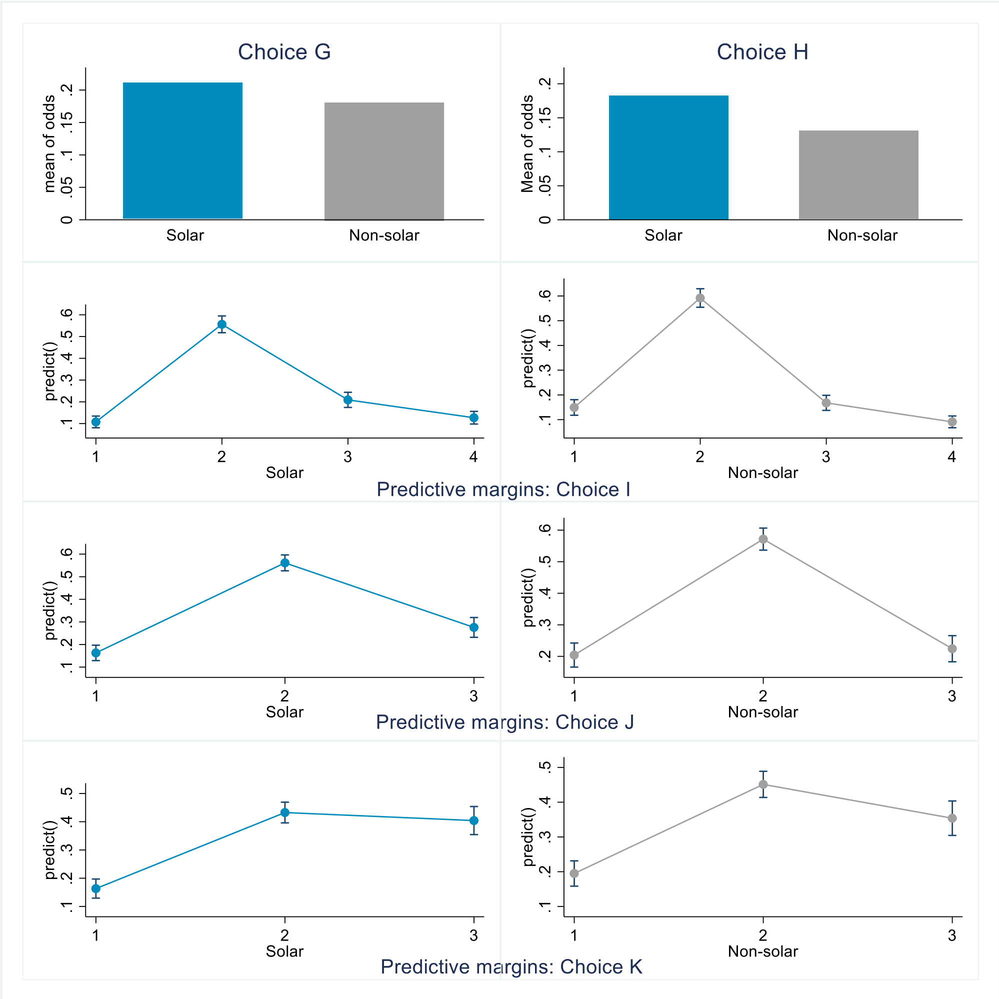


Figure 3. 7 Estimated risk perception and risk-taking behaviour levels for non-solar and solar groups.

Source: Authors' preparation.
Note: This figure presents the estimated logit and Ologit regression results in models 3.9-3.13 for non-solar and solar user groups. The first two graphs plot the means of odds ratios of logit models 3.9.a and 3.10.a for non-solar and solar groups. The next three graph-sets plot the predicted values of the probabilities of different levels of risk-taking behaviour.

Table 3. 13 The estimated cumulative risk-taking score.

	Risk-taking score		
	Model 3.14.a Full sample	Model 3.14.b High adoption areas	Model 3.14.c Low adoption areas
Variables	Coefficient	Coefficient	Coefficient
If a solar irrigation user	0.4946**	0.5766***	0.5724*
	(0.1783)	(0.2115)	(0.3407)
Farmer’s age	0.0041	0.0117	--
	(0.0058)	(0.0086)	
Farmer’s education	-0.0165	-0.0226	--
	(0.0152)	(0.0194)	
If the house is brick/tin/timber	0.1098	0.2571	--
	(0.2043)	(0.2246)	
Asset possession	-0.0447**	-0.0508*	-0.0419
	(0.0193)	(0.0258)	(0.0263)
Irrigation pump capacity	-0.0014	0.0161	-0.0294
	(0.0166)	(0.0173)	(0.0304)
If have any past investment experience*being a solar user	0.4764*	0.6081**	0.3398
	(0.2710)	(0.2829)	(0.2924)
Sample size	800	414	386
Prob > F	0.0005	0.0001	0.0855

Source: Authors’ calculation.

Note: This table reports the linear regression (Equation 3. 4) results for risk-taking scores for the full sample, sample in high adoption areas and the same in low adoption areas. For robustness analysis, a continuous risk score variable is estimated in an OLS regression model. The significant F-statistic in OLS regression shows that the model fits the data. Finally, the standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

3.4.4 Predicting the financial understanding level

The financial understanding level is constructed by combining the subjective and objective choices in the three experiments. The average financial understanding score is 8.42 (Table 3.2). Solar groups have a higher score (8.96) than the average, while the non-solar group’s score is 7.88. The estimated results of model 3.15.a in Table 3.14 (also presented visually in Figure 3.8) show that being a solar irrigation user increases the financial understanding score approximately by 1.21 (at the 1% significance level). The score improves (1.56) for solar users in high adoption areas. Solar users’ financial understanding is lower (0.95) in low adoption areas. The prediction magnitude increases if it is controlled for having any agricultural or non-agricultural investment experience (1.54 in model 3.16). The linear prediction of the financial understanding score remains robust in Model 3.17. Financial understanding increases the probability of being a solar user by 16.11 percentage points (at the 1% significance level). This indicates that considering the combined financial understanding, solar use impact is robust. Among the farm level characteristics in model 3.17, farmers' education, their house building materials like brick/tin/timber, and irrigation pump capacity have positive impacts on the likelihood of being a solar user.

3.4.5 Experimental validity

The credibility of this experimental design rested on the fact that each choice set is mutually exclusive. This is why, this study estimates each stated choice separately. Three different sets of props and follow-up questions are used so that farmers do not assume connections between choice sets. Variations in the probability results of making the stated choices reflect that forward-looking behaviour, understanding of calculation and opportunity costs, and risk-taking behaviour are exclusively affected by solar irrigation use. However, the stated choice is a random utility-maximizing behaviour based on hypothetical scenarios that may remain inconsistent. Farmers could make different choices in a similar situation or even if the situation changes. In such cases, often choices are compared between hypothetical and real situations (e.g., Luchini and Watson, 2014; Menapace and Raffaelli, 2021). Choice modelling is a strategy to process information (Louviere et al., 2005). Therefore, making choices within a time constraint could produce different results. It is also uncertain whether farmers had stated the same choices if they received monetary returns in this design. Monetary incentive itself could be a bias against making choices, either stated or revealed. Thus, monetary gains are kept hypothetical in this design. Another source of hypothetical bias is signalling (Menapace and Raffaelli, 2021). That is why farmers did not receive any indication about the three outcome variables in the choice sets and follow-up choice questions. They did not become cautious about their financial understanding or its three different parameters. Comparing two groups of farmers with similar covariate distribution also reduces any possible hypothetical bias. This even has implications for the internal validity of this design. For the experiment's external validity and inference, I have considered possible threats in i) sample size selection, ii) choice options, and generalization. Recruiting a sample of farmers across high and low solar network regions in 12 districts in Bangladesh ensures external validity. These districts are also diverse in solar installation models by public and private providers in Bangladesh. I have used a sample of solar and non-solar groups that are randomly and separately recruited with two balancing criteria. Cultivated land size (without homestead) distribution and cropping patterns are similar for both groups. For the validity of choice options, I pre-tested the design in one high solar network area and one low network area. This study also estimated the correlations controlled for an area dummy variable. An important caveat is that solar users neither purchase solar equipment nor own solar plants. As the analysis does not include pump ownership scenarios, it could overestimate the results. However, stated choices do not differ among non-solar users, i.e., between diesel and electricity users. Regarding pump ownership, solar, and electricity users follow the same irrigation setting, and the sample of diesel users does not include only pump owners. For this reason, ownership heterogeneity is not observed in this analysis.

Table 3. 14 The estimated financial understanding score.

Variables	Financial understanding score			Financial understanding score (controlled for any previous investment experience)	The probability of being a solar user estimated
	Model 3.15.a Full sample	Model 3.15.b High adoption areas	Model 3.15.c Low adoption areas	Model 3.16	Model 3.17
	Coefficients	Coefficients	Coefficients	Coefficients	Marginal effects
If a solar irrigation user	1.2101***	1.5699***	0.9518**	1.5368***	---
	(0.2273)	(0.2759)	(0.4664)	(0.4101)	
Farmer’s age	0.0072	-0.0022	-0.0130	0.0175	0.0024
	(0.0077)	(0.0120)	(0.0117)	(0.0216)	(0.0069)
Farmer’s education	-0.0079	-0.0251	0.0170	0.0411	0.0305*
	(0.0201)	(0.0256)	(0.0322)	(0.0393)	(0.0184)
If the house is brick/tin/timber	0.5519**	0.6152	0.5759	-0.1183	0.8805***
	(0.2690)	(0.3226)	(0.4168)	(0.5767)	(0.2520)
Asset possession	-0.0634**	-0.0492	-0.0760	-0.0338	-0.0211
	(0.0253)	(0.0350)	(0.0334)	(0.0508)	(0.0230)
Irrigation pump capacity	-0.0219	0.0078	-0.0501	0.0009	0.2780***
	(0.0220)	(0.0250)	(0.0445)	(0.0351)	(0.0207)
Financial understanding score	---			---	0.1610***
					(0.0322)
Sample size	800	414	386	138	800
Log-likelihood ratio	---	---	---	---	-405.11
Prob > chi2 or F	0.0000	0.0000	0.0163	0.0120	0.0000

Source: Authors’ calculation

Note: This table presents the results of the linear prediction (Equation 3. 4) of financial understanding, observed on the selected explanatory variables. The standard errors are in parentheses, and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. In models 3.16 the data are restricted to a farmer with any previous investment experience. For a robustness check to the linear prediction of financial understanding, the probability of being a solar irrigation user is estimated in the model (logit Equation 3. 1) 3.17. The result of the relationship between being a solar irrigation user and the financial understanding score is consistent with the OLS regression results with a significant F statistic.

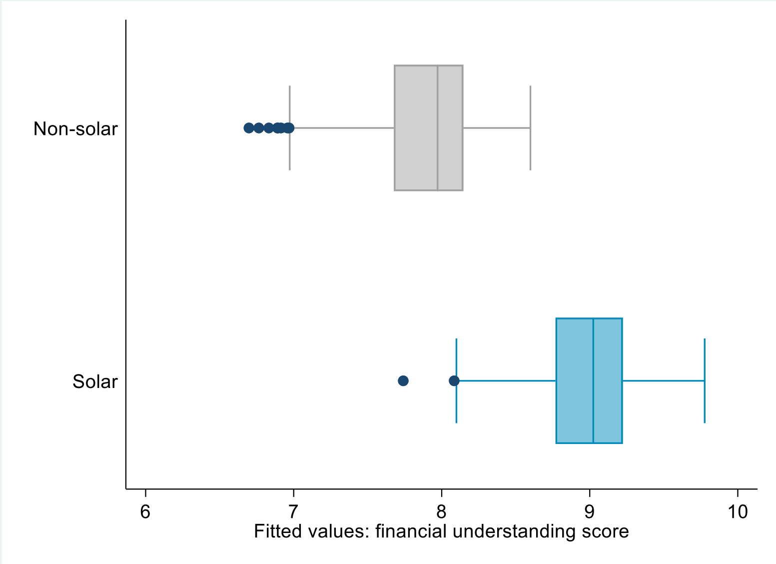


Figure 3. 8 Predicted financial understanding score for non-solar and solar groups.
Source: Authors' preparation.
Note: This figure presents the estimated linear prediction of the financial understanding score for solar adopters and non-adopters. This figure is prepared from the outputs of model 3.15.a.

3.5 Conclusion

Using three different experimental designs demonstrating subjective and objective choice sets, this study analyses the impact of solar irrigation use on farmers' financially forward-looking behaviour, the understanding of calculation and opportunity costs, and finally the risk perception and risk-taking behaviour. These three factors or levels are then combined to determine the financial understanding score. The main findings suggest that the use of solar irrigation increases the probability of the stated choices towards being forward-looking, being able to understand the calculation, and developing risk-taking behaviour. Such attitudes improve with a higher solar network intensity. Similarly, the cumulative of all the parameters, i.e., financial understanding is also improved for solar user farmers. In the first level, farmers using solar irrigation stated their preference for a box of small balls, and return in 7 days at the same rate and different rates, indicating financially forward-looking behaviour. Most of them perceived that such choices explain long-term and a larger return. In the second level, solar users are more likely to understand calculation and opportunity costs. However, the visibility of the box with a higher value dominates such preference irrespective of the irrigation energy type. In the third level, solar users tend to make high-risk-return choices. Such risk-taking behaviour also varies with reward type. On the whole, the results suggest that solar users have a better cognitive ability of their choices than non-adopters. Among the farm characteristics, brick/tin/timber-built houses, farmer's age, previous investment experiences, irrigation pump size, the land amount in possession, and high solar networks in the area strongly impact such choices and influence the financial understanding score.

The findings of this study have some significant implications. Results show that the actual adoption of sustainable technology improves financial understanding. This is important for deriving sustainable energy transition planning. Financial education and investment experience are useful in increasing the adoption rate. While controlled for farmers' sustainable practices in the understanding model, the sign on the coefficient is not expected. This suggests that farmers' sustainability perception may trigger both financial understanding and a technology switch. Therefore, institutions can use experienced adopters to improve potential users' cognitive ability (i.e., financial understanding). Institutional demonstrations in this regard could use this experimental design. As for further explanation and inquiry, farmers' stated choices could be compared with and without time constraints. Farmers' stated preferences also may vary with the length of technology use. For example, the behaviour and understanding of experienced adopters could be more consistent throughout the choices than the recent adopters. The average length of solar irrigation use is approximately 4 years, which did not affect the stated choices in this study. The regression processes do not confirm if financial understanding improves or deteriorates after using solar irrigation. This study intended to find intrinsic financial understanding, hence I did not consider the period of using solar irrigation. Experiencing any crop productivity shock, livelihood loss and any idiosyncratic shock (illness or death of an earning household member) may affect farmers' risk-taking behaviour. Finally, it would be interesting to analyse financial understanding heterogeneity across various sustainable on-farm practices e.g., water-efficient methods, organic methods, multiple adoptions, single adoption, and so on.

Appendix A
Additional graphs and tables for financial understanding

Appendix A.1 ROC analysis of logit models

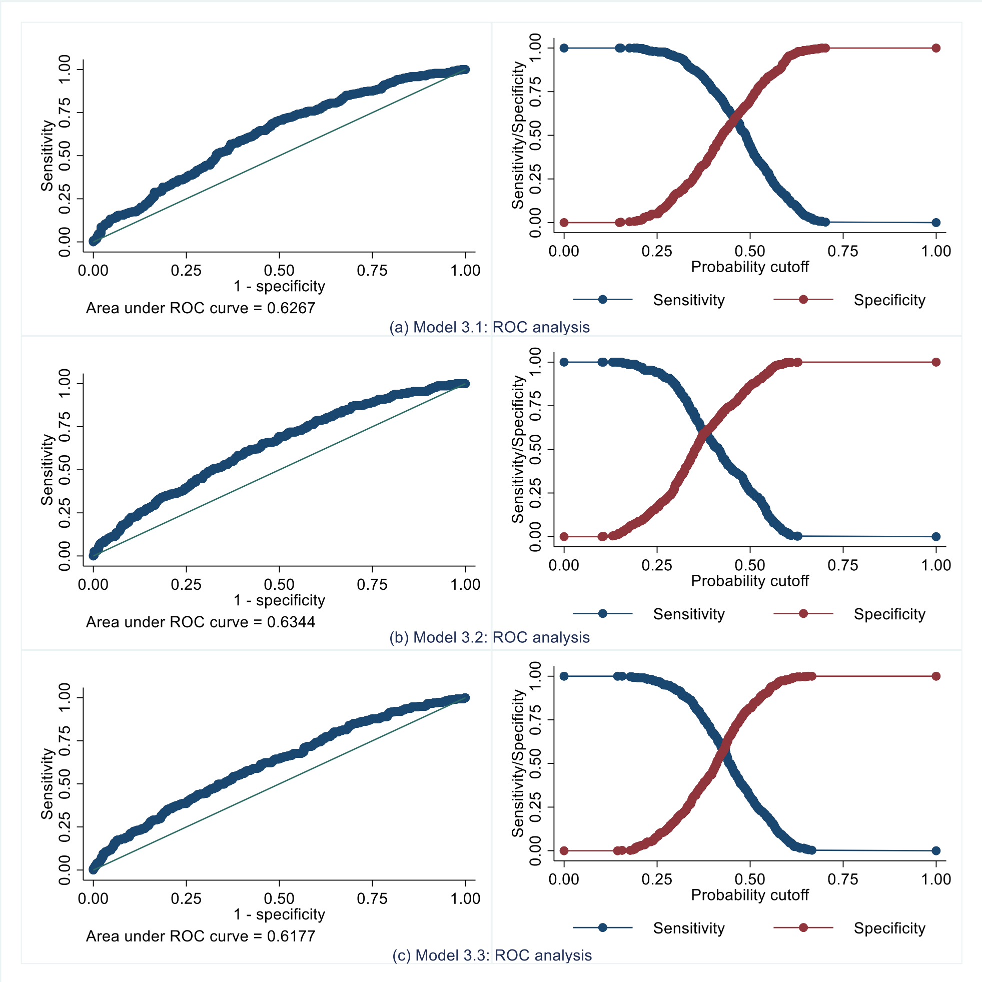


Figure A. 1 ROC analyses of Model 3.1.a, Model 3.2.a and Model 3.3.a.
Source: Author's preparation.
Note: This figure depicts the post estimation ROC analyses of the three forward-looking probability (logit) models, Model 3.1.a, Model 3.2.a and Model 3.3.a. Regarding the ROC comparisons, the second model, Model 3.2.a has the highest credibility in estimating the probability of choosing returns in multiple periods (Choice B).

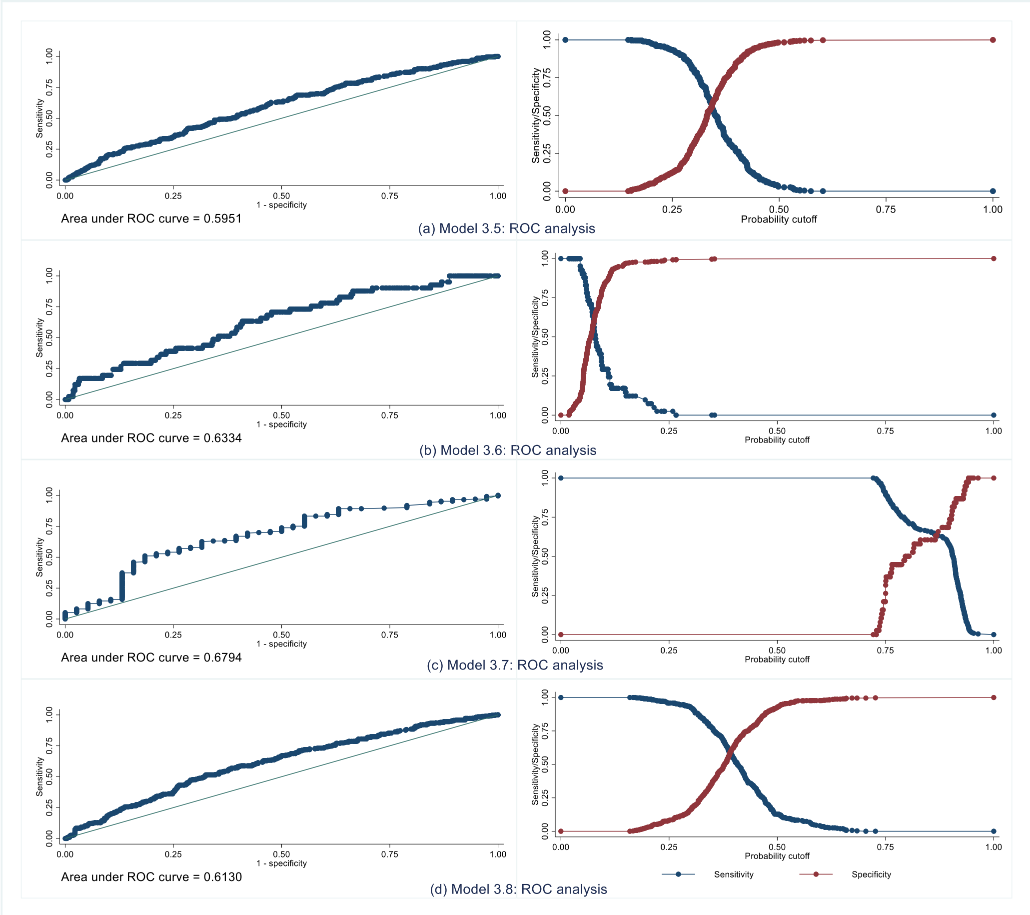


Figure A. 2 ROC analyses of Model 3.5.a, Model 3.6.a Model 3.7.a and Model 3.8.a.
Source: Author’s preparation.
Note: This figure depicts the post estimation ROC analyses of the for logit models to estimate the probability of understanding ability in Models 3.5.a, 3.6.a, 3.7.a and 3.8.a. Based on the ROC comparisons, Model 3.7.a has the highest credibility in estimating the probability of switching to a higher-valued transparent box.

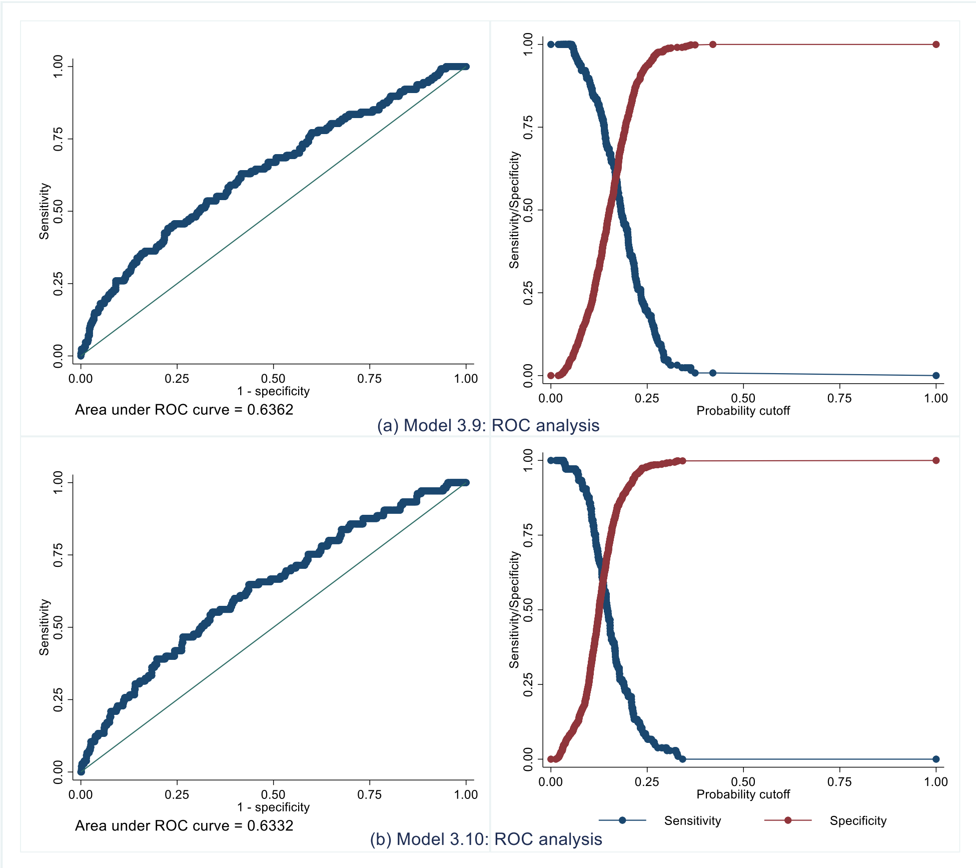


Figure A. 3 ROC analyses of Model 3.9.a and Model 3.10.a.
Source: Author's preparation.
Note: This figure depicts the post estimation ROC analyses of the risk-taking subjective choice logit models, Model 3.9.a and Model 3.10.a. Both models have nearly equal credibility in estimating the probability of choosing a box with a broken bottom.

Appendix A.2 Generalized logit models and margins analyses of outcome variables

Table A. 1 GOlogit model results for the financially forward-looking behaviour choices and levels.

Variables	Forward-looking behaviour (constructed)		
	Probability of outcome 1 vs outcomes 2, 3, 4	Probability of outcomes 1 and 2 vs outcomes 3 and 4	Probability of outcomes 1,2,3 vs outcome 4
If a solar irrigation user	0.4379**	0.7812***	1.3615***
	(0.1713)	(0.1742)	(0.1941)
Farmer's age	-0.0140**	-0.0140**	-0.0140**
	(0.0054)	(0.0054)	(0.0054)
Farmer's education	0.0102	0.0102	0.0102
	(0.0139)	(0.0139)	(0.0139)
If the house is brick/tin/timber	0.5659***	0.5659***	0.5659***
	(0.1902)	(0.1902)	(0.1902)
Number of rooms	-0.0718	-0.0718	-0.0718
	(0.0535)	(0.0535)	(0.0535)
Asset possession	-0.0257	-0.0257	-0.0257
	(0.0195)	(0.0195)	(0.0195)
Irrigation pump capacity	-0.0248	0.0248	-0.0248
	(0.0154)	(0.0154)	(0.0154)
Log-likelihood ratio		-982.88602	
Prob > chi2		0.0000	

Source: Authors' calculation.
Note: This table reports the generalized ordered logit model results for the observed forward-looking behaviour levels. The standard errors are in parentheses and *** p < 0.01, ** p < 0.05, * p < 0.10.

Table A. 2 GOlogit model results for four levels of risk-taking behaviour.

Variables	Risk-taking behaviours in Choice I		
	Probability of outcome 1 vs outcomes 2, 3, 4	Probability of outcomes 1 and 2 vs outcomes 3 and 4	Probability of outcomes 1,2,3 vs outcome 4
If a solar irrigation user	-0.0953	0.5634***	0.5216*
	(0.2613)	(0.1903)	(0.2912)
Farmer's age	-0.0051	0.0093	0.0014
	(0.0083)	(0.0063)	(0.0091)
Farmer's education	-0.0120	-0.0147	-0.0559**
	(0.0221)	(0.0166)	(0.0249)
If the house is brick/tin/timber	-0.4663	0.0647	0.1302
	(0.3457)	(0.2209)	(0.3461)
Asset possession	-0.0082	-0.0084	0.0064
	(0.0288)	(0.0209)	(0.0267)
Irrigation pump capacity	0.0281	0.0160	-0.0184
	(0.0256)	(0.0178)	(0.0294)
	1.6936**	0.6661**	-0.0544
	(0.7374)	(0.2683)	(0.4157)
Log-likelihood ratio		-887.67	
Prob > chi2		0.0000	

Source: Authors' calculation.
Note: This table reports the generalized ordered logit model results for the observed risk-taking behaviour levels of Choice I. The standard errors are in parentheses and *** p < 0.01, ** p < 0.05, * p < 0.10.

Table A. 3 GOlogit model results for three levels of risk-taking behaviours in Choice J and Choice K.

	Risk-taking behaviours in Choice J		Risk-taking behaviours in Choice K	
	Probability of outcome 1 vs outcomes 2, 3	Probability of outcomes 1, 2 vs outcome 3	Probability of outcome 1 vs outcomes 2, 3	Probability of outcomes 1, 2 vs outcome 3
solar	0.4917**	0.4504*	0.0898	0.0910
	(0.2302)	(0.2334)	(0.1964)	(0.1776)
q212_farmer_age	-0.0017	-0.0008	0.0060	0.0074
	(0.0076)	(0.0075)	(0.0067)	(0.0060)
q214_farmer_education	-0.0004	-0.0145	-0.0373**	0.0102
	(0.0201)	(0.0201)	(0.0183)	(0.0158)
house	-0.2168	-0.3085	0.4382*	0.0526
	(0.2834)	(0.2807)	(0.2443)	(0.2047)
asset	-0.0290	-0.0302	-0.0405*	-0.0525***
	(0.0239)	(0.0258)	(0.0227)	(0.0202)
q39_pump_capacity	0.0199	0.0213	0.0193	0.0067
	(0.0214)	(0.0213)	(0.0183)	(0.0164)
invest	1.8101*	1.8769**	-0.4305	0.5288**
	(0.7368)	(0.7369)	(0.3353)	(0.2684)
Log-likelihood ratio	-758.4203		-809.887	
Prob > chi2	0.0000		0.0004	

Source: Authors' calculation.

Note: This table reports the generalized ordered logit model results for the observed risk-taking behaviour levels of Choices J and K. The standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A. 4 Results for the group-wise margins of subjective choices.

Subjective choices	Solar	Non-solar	Difference
Choice A: big ball (0) vs small balls (1)	0.5562	0.3470	0.2092
	(0.0271)	(0.0258)	(0.0408)
Choice D: money now (0) vs money later (1)	0.3938	0.2896	0.1041
	(0.0276)	(0.0246)	(0.0405)
Choice G: Big ball (0) vs possible broken box of small balls (1)	0.2024	0.1258	0.0766
	(0.0254)	(0.0168)	(0.0338)
Choice H: Big ball (0) vs surely a broken box of small balls (1)	0.1943	0.0892	0.1050
	(0.0267)	(0.0139)	(0.0331)

Source: Authors' preparation

Note: This table presents the margins (predicted) of subjective choices in favour of the choice-making of small balls, money later, a possible broken box of small balls and surely a broken box. The last column reports the difference in margins and the associated standard errors. The margins are produced by estimating Model 3.1, Model 3.5, Model 3.9, and Model 3.10. All margins are highly significant (at the 1% significance level). The standard errors are in parentheses. Outcomes in all models are controlled for the selected covariates. The covariates include household's asset quantity, if the house is made of brick/tin/timber, number of rooms, farmer's age and education, and irrigation pump capacity.

Table A. 5 Results for the group-wise margins of objective choices.

Objective choices	Solar	Non-solar	Difference
Choice B: return in one day (0) vs return in 7 days (1)	0.4656 (0.0274)	0.2991 (0.0250)	0.1664 (0.0406)
Choice C: return in one day (0) vs return in 7 days at different rates (1)	0.5002 (0.0274)	0.3428 (0.0258)	0.1573 (0.0411)
Choice E: switching to the solid box (no=0 and yes=1)	0.1199 (0.0273)	0.0504 (0.0128)	0.0695 (0.0326)
Choice F: switching to the transparent box (no=0 and yes=1)	0.9158 (0.0247)	0.7954 (0.0419)	0.1204 (0.0525)
Choice I: Risk-taking behaviour: no participation	0.1004 (0.0120)	0.1589 (0.0160)	-0.0584 (0.0158)
Choice I: Risk-taking behaviour: a sure gain	0.5441 (0.0191)	0.5990 (0.0185)	-0.0548 (0.0145)
Choice I: Risk-taking behaviour: low risk and return	0.2181 (0.0172)	0.1586 (0.0143)	0.0594 (0.0157)
Choice I: Risk-taking behaviour: high risk and return	0.1372 (0.0148)	0.0833 (0.0106)	0.0538 (0.0137)
Choice J: Risk-taking behaviour: no participation	0.1547 (0.0153)	0.2138 (0.0187)	-0.0590 (0.0206)
Choice J: Risk-taking behaviour: low risk and return	0.5580 (0.0179)	0.5719 (0.0177)	-0.0138 (0.0071)
Choice J: Risk-taking behaviour: high risk and return	0.2871 (0.0208)	0.2142 (0.0187)	0.0729 (0.0255)
Choice K: Risk-taking behaviour: no participation	0.1517 (0.0149)	0.2081 (0.0183)	-0.0563 (0.0197)
Choice K: Risk-taking behaviour: low risk and return	0.4222 (0.0184)	0.4589 (0.0186)	-0.0366 (0.0122)
Choice K: Risk-taking behaviour: high risk and return	0.4259 (0.0232)	0.3329 (0.0225)	0.0930 (0.0307)

Source: Authors' calculation

Note: This table reports the margins of outcome variables for solar adopters and non-adopters. The last column shows the difference in coefficients. The margins are produced estimating Model 3.2, Model 3.3, Model 3.6, Model 3.7, Model 3.11, Model 3.12, and Model 3.13. The standard errors are in parentheses. All coefficients are significant at the 1% significance level except for the group differences for Choice E and Choice F (at the 5% level), and Choice J (low risk-return at the 10% level,). Outcomes in all models are controlled for the selected covariates. The covariates include household's asset quantity, if the house is made of brick/tin/timber, number of rooms, farmer's age and education, and irrigation pump capacity.

Appendix A.3 Visualization of the subjective choice experiments

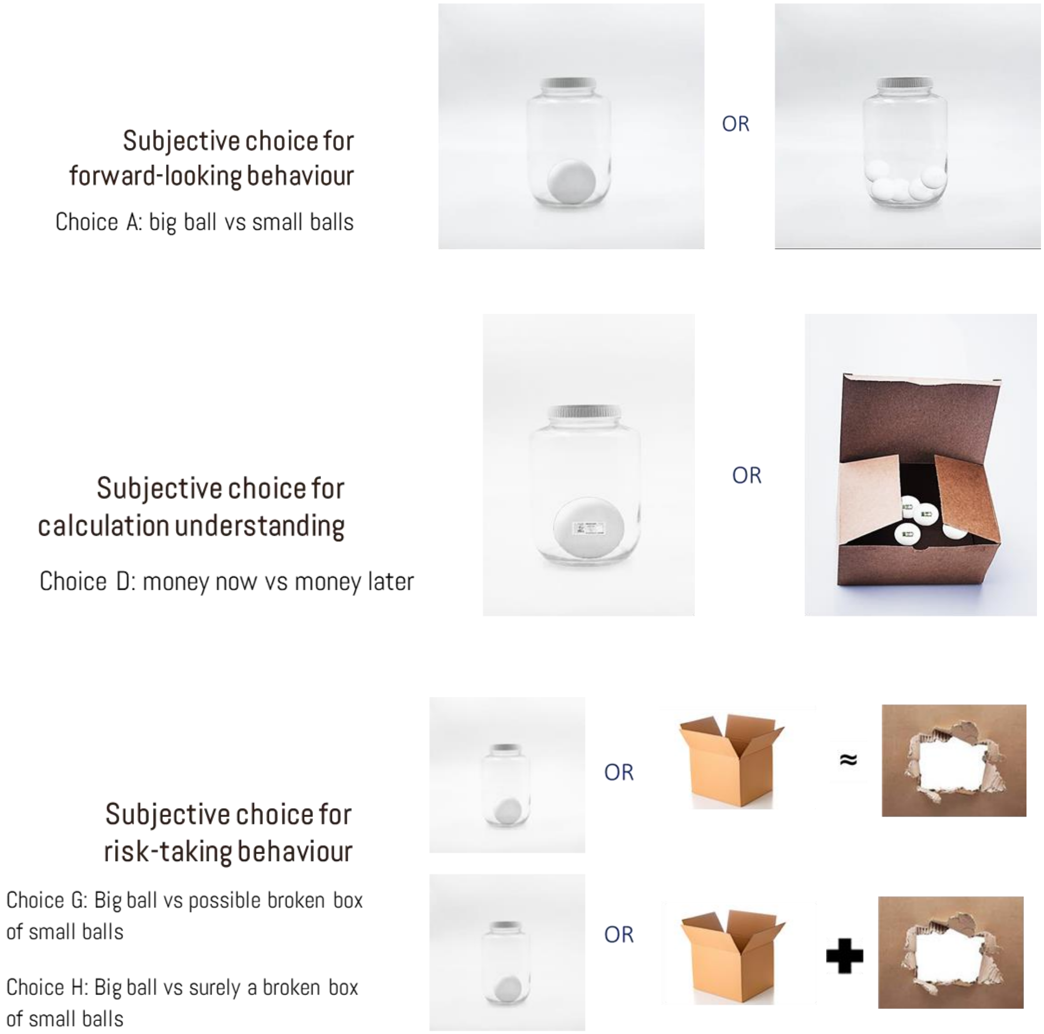


Figure A. 4 Visualization of the three subjective choice experiments.
Source: Author's preparation.
Note: This figure depicts three subjective choice experiments' options presented to farmers.

Chapter 4

Farmers' pro-environmental behaviour for renewable technology

4.1 Introduction

If technology ensures socio-economic benefits and reduces negative impacts on the environment simultaneously, its adoption decision is a pro-environmental behaviour (Detenber et al., 2018). Climate-smart technology is a pro-environmental approach to the food-environment nexus, holistically contributing to productivity gains, social benefits, and environmental safety. However, the necessity of a sustainable technology could merely remain a normative understanding in academic scholarship and policy arenas. The reason is that implementation is at an adopter's discretion and that the decision-making process is clouded by perceptions and actions. Farmers may prioritize structural and ecological conditions over financial factors because of their dependence on nature. Kim et al. (2021) stated that pro-environmental actions resemble an individual being conservative or liberal. Some recent studies also suggest that ability, knowledge, and information (Adnan et al., 2017; Adnan et al., 2020), increase such actions by improving *cognitive fluency* (Alter and Oppenheimer, 2009), and yet, environmental motivation and orientation could exert an impact. The learning process of a new technology indeed requires motivation. Even reverting to previous technology is a tendency if the experience of new technology is not satisfactory (Bijttebier et al., 2018). Psychological efficacy and socio-demographic variables influence farmers' adoption decisions when alternative technology choices are available (Bakker et al., 2021). In such cases, perceptions may not necessarily induce the adoption of climate-smart technology and decision-making becomes more capricious. Therefore, adopters' technology choice can explain the complementarity of their perceptions and pro-environmental behaviour in action.

To evaluate the technology adoption behaviour, previous studies mostly use financial or optimization scenarios. Financial optimization or production benefits are not sufficient to stir up sustainable actions. Given the increasing exposure of low-carbon technologies in academics and policy arenas, adopters may be concerned with the impacts of their cost-effective technology choice on the environment. For instance, Conradie et al. (2021) showed that strong intentions and positive attitudes toward renewable energy influence the willingness to pursue its use. Renewable energy use even enhances the quality of environmental information (Toledo, 2016), and yet sustainable decisions require persuasion (Gosnell, 2018). In this regard, there is a scope to evaluate if renewable technology adoption is action- or perception-oriented pro-environmental behaviour or both and what type of actions evoke the nature of environmental motivation of users. In this respect, farmers' actions include on-farm and off-farm sustainable activities.

This study seeks to evaluate the effect of technology adoption on farmers' pro-environmental behaviour and the nature of environmental motivations. The strategy is to evaluate pro-environmental perception, behaviour, motivation and action comprehensively, i.e., to compare perception, motivation and behaviour of solar and non-solar irrigation users. Irrigation in Bangladesh is highly resource intensive. Summer and dry seasons use intensive irrigation and even in monsoon crops need supplementary irrigation because of variable rainfall trends. Consequently, an increasing water scarcity and excessive use of chemicals threaten yields and food security in the country (Alauddin and Sarker, 2014; Alauddin et al., 2021). Farmers perceive that they lose production because of climate change and environmental challenges (Islam et al., 2017). Thus, farmers can be wary of irrigation impacts on resources, and irrigation technology may explain their pro-environmental perception and behaviour. The specific objectives of this study are to evaluate- i) farmers' pro-environmental behaviour, ii) the type of their environmental motivations and behavioural consistency, and iii) the correlations of choices and motivations with sustainable on-farm and off-farm action-behaviour. To elaborate, this study estimates the possibility of farmers' coherent pro-environmental actions in sustainable farming, crop residue management, household waste management, and general perception of renewable energy. The conceptualization of pro-environmental behaviour uses the framing ideas of Detenber et al. (2018). The methodological approach includes choice experiments with competing framing methods that reflect perceptions, motivations, and actions.

This chapter proceeds as follows. Section 4.2 discusses the framework to understand pro-environmental behaviour in adoption decisions. Section 4.3 provides a detailed description of the experimental design, empirical models, and sample characteristics, followed the empirical results and discussions in Section 4.4. Section 4.5 concludes this chapter by providing a summary of the results and implications.

4.2 Framework for pro-environmental behaviour in adoption decisions

This section discusses the existing behavioural frameworks to theorize sustainable technology adoption including nonparametric and experimental approaches. The intention is to observe the factors shaping sustainable attitudes and the pathway that motivates action-behaviour. Two notable framework in the past studies to understand adoption behaviour are the Theory of Planned Behaviour (TPB) and the Theory of Reasoned Action (Ajzen, 1991; Fishbein and Ajzen, 1975). According to these frameworks, *intention* explains technology uptake, which depends on *attitude* because of potential outcomes. For instance, Hyland et al. (2018) observed that *high adopters* possess more positive attitudes toward sustainable grassland management techniques than *low adopters* concerning milk quality, grass quantity, and production. Their results also demonstrate that behavioural intention relies upon farm size, resource position, and knowledge about the technique. If technology does not ensure economic and environmental gains equally or complementarily (Balaine et al., 2020) and any certainty about future outcomes (Barnes et al., 2019), farmers may not be interested in adoption. Adnan et al. (2020) demonstrated that the perception of foreseeable impacts on resources and the environment motivates green fertilizer use. Bakker et al. (2021) argued that use of pesticide reduces because of their environmental concerns about soil and water quality, human health, and yield quantity and quality. Bijttebier et al. (2018) observed that farmers who are positive towards non-inversion tillage, emphasize soil nutrients, fuel-use reduction, and water savings. This implies that adopters are concerned about what technology offers to protect the environment and resources. The authors also found that adoption rate is high in areas where farmers have such concerns.

Although TPB and TRA could predict the channels in the decision-making process, components remain indirect and subjective in estimation. Such components are unobservable, hence latent variables are utilized by constructing statements (Li et al., 2020). Such statements often do not reflect adopters' pro-environmental behaviour objectively and the effect of known attributes of the technology. For instance, in Daxini, Ryan, O'Donoghue, and Barnes (2019), four traits construct *attitude* components, namely usefulness, reliability, and credibility of ideas, and significance of nutrition management practice, and yet the features are not technology-specific. *Intention* predicting behaviour is endogenous, often produces mixed results, and actual behaviour could remain underestimated. Detenber et al. (2018) demonstrated that *behavioural intention* is merely suggestive and hence less effective in cognitive understanding. Daxini et al. (2018) opined that *mandatory adopters* did not perceive any environmental damage. Bijttebier et al. (2018) found that non-adopters showed larger intentions than adopters of non-inversion tillage. In their study, TPB components are stated in terms of future or projected contexts. Therefore, it could not elucidate the causes of adopters' structural perception and their variable socio-environmental concerns due to actual actions, e.g., on-farm and off-farm activities. Past evidence suggests that social and institutional capital has motivated intention and behaviour in many cases (Bakker et al., 2021; Conradie et al., 2021; Daxini et al., 2019; Hyland et al., 2018; Li et al., 2020). Variables measuring household or farm characteristics are not included directly in these studies. Various inputs and information channels trigger environmental motivation (Ballantyne et al., 2021). Demonstrations may alter perception and inspire practice, and helps transform motivation into behaviour. In contrast, Gosnell (2018) found that pro-environmental message intervention did not increase pro-environmental uptake of an online billing system. Czap et al. (2019) found no effect of the environmental message on conservation programme enrolment. Information campaigns and awareness do not necessarily confirm actual adoption. It is also possible that there is heterogeneity due to any experience of previous sustainable behaviour. Earlier evidence in the TPB framework did not estimate the impact of experience and complementarity of sustainable practices.

Environmental action-behaviour has also increasingly used choice experiments, especially in comparative research, and impact evaluations (Chèze et al., 2020). Recent experimental designs analyse the variations in psychological response towards technology if the presentations of attributes are different. For instance, Amatulli et al. (2019), observed that negative consequences have a stronger effect than positive attributes, on supporting an environmental cause, through a cognitive feeling of shame. The reason might be that pro-environmental behaviour varies with the type of messages received and how the messages are evaluated by users (Ballantyne et al., 2021). Kim et al. (2021) argued that there are differences in the impacts of pro-environmental messages with temporal attributes. Their study found that environmental messages concerning the future motivate *liberal* individuals more than the messages tied to the past. Such differential impacts of messages are observed due to costs and institutional support (Detenber et al., 2018). In Czap et al. (2019) an empathy message inspired farmers to sign up for conservation programmes. They also explained that empathy messages rather acted as an information channel than as a booster for conservation behaviour. Gosnell (2018) utilized a frame separately to depict environmental concerns, yet their framing contained persuasive messages about environmental benefits. It appears that there is heterogeneity in expressing pro-environmental behaviour and motivations may change.

In the technology adoption pathway, the perception of adverse impacts on resource quality generally encourages sustainable behaviour. Previous findings suggest that adopters' concern led by perception often determines the prospect of technology. Nevertheless, the perception of negative consequences on the environment does not always reduce unsustainable actions (Chèze et al., 2020). One reason might be that financial and environmental motivations are not separate in the evidence. Moreover, sustainability perceptions that are irrelevant to action/behaviour may not induce the adoption of sustainable technology. Environmental concerns can exclusively steer technology adoption decisions, instead of financial optimization or even resource positions. It can also be *environmental psychology,* which can be understood through the lens of an adopted technology. In this regard, relevant actions of farmers include both on-farm and off-farm sustainable practices. Thus motivated by the diverse response variations towards environmental choices and sustainable actions, I construct the choice experiments with objects and messages in an inverse framing style. Both objects and messages reflect behaviour and motivations. To be precise, I operationalize pro-environmental behaviour sustainable on-farm technology adoption, and off-farm activities.

4.3 Methods and research design

4.3.1 Experimental design

This study administers choice experiments using three mutually exclusive frames and competing frames to evaluate pro-environmental behaviour and the nature of environmental motivations. Different presentations of frames were originally explained in Tversky and Kahneman's *Prospect Theory* (Kahneman and Tversky, 2013). They argue that cognitive evaluation varies with connotations and the use of different frames captures this effect while contexts may remain the same. For instance, a handwritten original message is more effective than a reproduced photocopy version in encouraging conservation programme enrolment in Czap et al. (2019). In a recent study, multiple audio-visual landscape frames are used presenting a large and small number of renewable energy plants respectively, to analyse variable psychological reactions to landscape choice and renewable energy use (Spielhofer et al., 2021). Kahneman (2003) explains that perception is shaped by natural assessments including physical properties of objects. Thus, framing helps to understand perceptions both subjectively and objectively. Moreover, using multiple frames, it is possible to elucidate these perceptions separately. Regarding this, for dialectic cognitive understanding and evaluation of an environmental scenario, *competing frames* are more useful (Detenber et al., 2018). Unlike *complementary frames*, the authors argued, competitive frames are bi-directional and do not contain information that can be persuasive in either direction, i.e., inputs in two frames commonly are of equal importance. The dispositions in both frames demonstrate the cognitive consistency of a participant by comparing inverse perspectives. This suggests that frames can be compared to explain the construction of ultimate behaviour. In this study, I construct the frame sets focusing on objects and purposeful messages.

In this experimental setting, surveyors show farmers three frame sets and each frame set contains two competing bundles of objects and/or messages. Surveyors ask them to choose one bundle from each frame set. The first frameset mainly uses objects, while the second and the third frame sets emphasize the messages conveyed along with the bundles of objects. Each frame set identifies an attribute with two options. The first frame set can determine pro-environmental attitude attributes and the second and the third sets can explain two environmental motivation attributes. In the first frameset, farmers choose between a pro-environmental bundle and a not-pro-environmental bundle. Bundle 1 includes environment-friendly and sustainable objects and Bundle 2 includes unsustainable objects. Figure 4.1 depicts the objects and frames for the first choice experiment. In this experiment, I test the following hypothesis:

H4.1: Solar users are more likely to choose a pro-environmental bundle, than non-solar users.

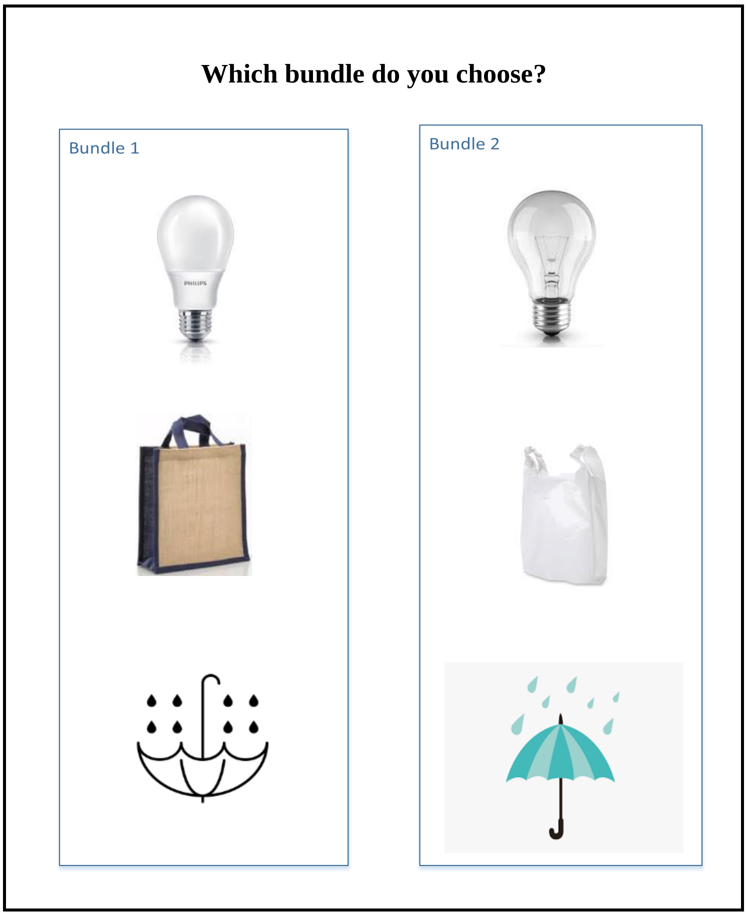


Figure 4. 1 The first frame set of pro-environmental choice-making decision.
Source: Author's preparation.
Note: This figure presents the first frame set containing pro-environmental and not environmental objects. Bundle 1 (pro-environmental) contains (from the top) an energy-saving bulb, a jute bag, and an umbrella collecting rainwater. Bundle 2 (not environmental) contains (from the top) a regular bulb, a poly bag, and an umbrella to use when it is pouring.

In the second experiment, farmers choose between two environment-friendly bundles. Each bundle relays a text message. Inversely framed messages contain two types of environmental motivations, i.e., motivation to save resources and motivation to control loss of resources. The message for Bundle 3 shows- "You surely save energy and water by 20%". Bundle 4 shows the message conveying the possibilities of loss mitigation in resource use. The message precisely is, "You may control loss of energy and water by 80%". Figure 4.2 shows the details of the frames and objects. Messages also differ in the levels (surety versus possibility) of resource management. Thus this experiment tests if motivations for environmental protections, i.e., saving resources and controlling resource loss depend on energy use. This will show if motivations vary between solar and non-solar users. I test the following hypothesis:

H4.2: Environmental motivations (resource loss control and resource saving) vary between irrigation technologies.

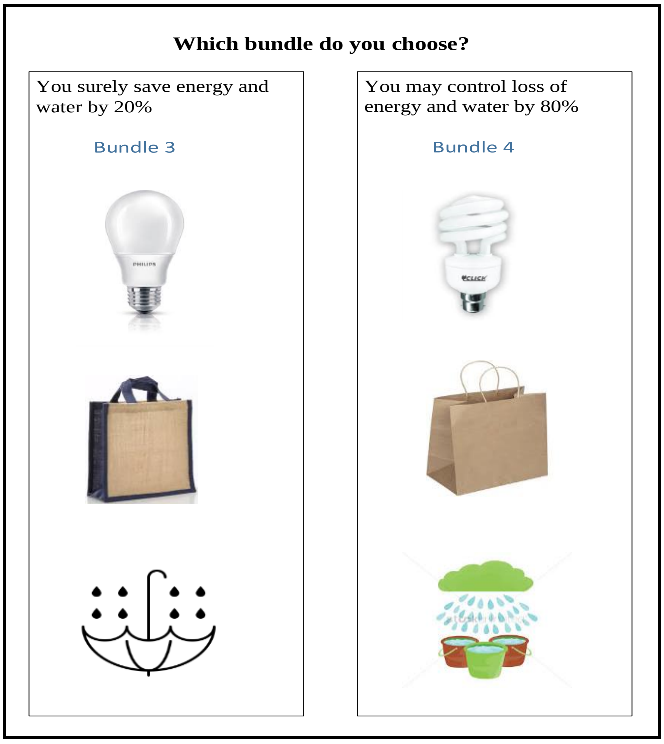


Figure 4. 2 The second frame set of environmental motivations with different messages.
Source: Author's preparation.
Note: This figure presents the second frame set containing environmental motivations in messages. Bundle 3 contains (from the top) an energy-saving bulb, a jute bag, and an umbrella collecting rainwater with an energy-saving (by 20%) message. Bundle 4 contains (from the top) a different energy-saving bulb, a paper bag, and three buckets storing rainwater in bulk and the message is the possibility to control energy loss by 80%.

Farmers, while looking at the second frame set choices, may show cognitive bias towards volume significance (20% versus 80%) and message contents (savings versus loss control). That is why, a third set of frames in the following experiment is given to farmers. Keeping similar objects of Figure 4.2, messages are presented respectively as "You surely save energy and water by 50%" for Bundle 5 and "You may control loss of energy and water by 50%" for Bundle 6 (Figure 4.3). By adding this frame, I compare choices in these two sets due to the changes in proportions. Thus, I test here whether motivations are variable or consistent and if motivations depend on message contents, i.e., the test of the framing effect. I test as follows:

H4.3: The consistency and variability of environmental motivations depend on irrigation technology use.

H4.4: Environmental motivations depend on the content of messages.

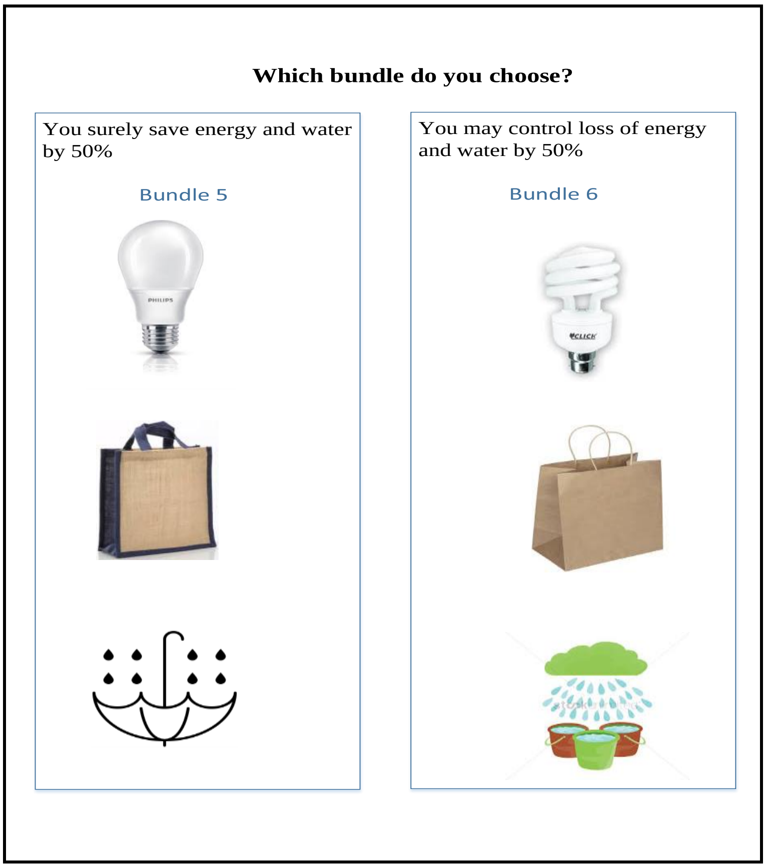


Figure 4. 3 The third frame set of environmental motivations with similar messages.
Source: Author's preparation.
Note: This figure presents the third frame set containing environmental motivations with similar messages. Bundle 5 contains (from the top) an energy-saving bulb, a jute bag, and an umbrella collecting rainwater with an energy-saving message. Bundle 6 contains (from the top) a different energy-saving bulb, a paper bag, and three buckets storing rainwater in bulk and the message shows the possibility to control energy loss. In both cases, the volume is 50%.

The experiments in this study assumes that a participant's response is less likely to be triggered by unknown expectations or scenarios and hence their choice-making could be efficient. The selection of the objects for the experiments considers, i) resource-use efficiency, and ii) any sustainable behaviour in daily life. The bundles include known, relevant, and available objects in study area, so no pre-demonstration is required. Even while reading out the messages by surveyors in the second and the third frame sets, farmers do not receive any indication of the significance of the messages. Nevertheless, participants are asked if they are familiar with the objects shown. Three experiments and frames are mutually exclusive so that I can estimate the probability of the choice-making and at the same time evaluate the framing effects. Multi-dimensionality in terms of a larger number of choice tasks is commonly used in discrete choice experimental (DCE) designs for the valuation of environmental goods (e.g., Abdu et al 2022; Davies et al 2023; Vallejo-Torres et al., 2020). Such designs use utility maximization components in attribute levels and various attributes are combined to identify optimum preferences in multiple-choice tasks for the sake of *choice consistency* and *efficiency* (Mariel et al., 2021). When attributes are correlated, it is possible to evaluate them at various levels, i.e., how much of an attribute is traded off to receive another attribute. However, such a trade-off does not conclusively elucidate a single attribute's effect. As Kahneman (2003) explained, perception is effortless and rapid or effortful based on the pace of mind processing, while intuition is inflicted by known and unknown expectations. Random choice manipulation tasks require intuitions, and participants can be intuitive after a few rounds of manipulation. In addition, manipulation of choice tasks in different combinations may or may not ensure choice consistency because of the embedded cognitive complexity in tasks (e.g., Kehlbacher et al, 2013). This study seeks to explore intrinsic behaviour and motivations which require action-oriented perceptions instead of intuition. In this study, attributes (pro-environmental attitude and motivations) are not combined and different levels or rankings of each attribute are not used in one frame. Therefore, I have not conducted manipulation tasks in the choice-making processes.

4.3.2 Models

4.3.2.1 Outcome variables

Pro-environmental behaviour and environmental motivations

This study analyses the outcome variables in two stages (Figure 4.4). In the first stage of empirical analysis, the outcome variables include a pro-environmental attribute and two attributes for motivations. Pro-environmental bundle choice (Bundle 1) in the first frame set is coded 1 and 0 otherwise. Code 0 is used for the not-pro-environmental bundle. While estimating the motivations, code is 1 for making the choice of control resource loss by 80% (Bundle 4) in the second frame set and for making the choice of control resource loss by 50% (Bundle 6) in the third frame set. In the second stage of analysis, the strategy is to evaluate the consistency of motivations by estimating the framing effects attributes. I construct three attributes from the stated preferences. Farmers can choose to save resource or to control resource loss in both the second and the third frame sets. Farmers also may switch choices between these two sets. Thus, three exclusive categories are found and the codes are as follows:

$$1 = if\ choose\ to\ save\ resource$$

$$2 = if\ choose\ to\ control\ resource\ loss$$

$$3 = if\ switch\ choice\ for\ proportion$$

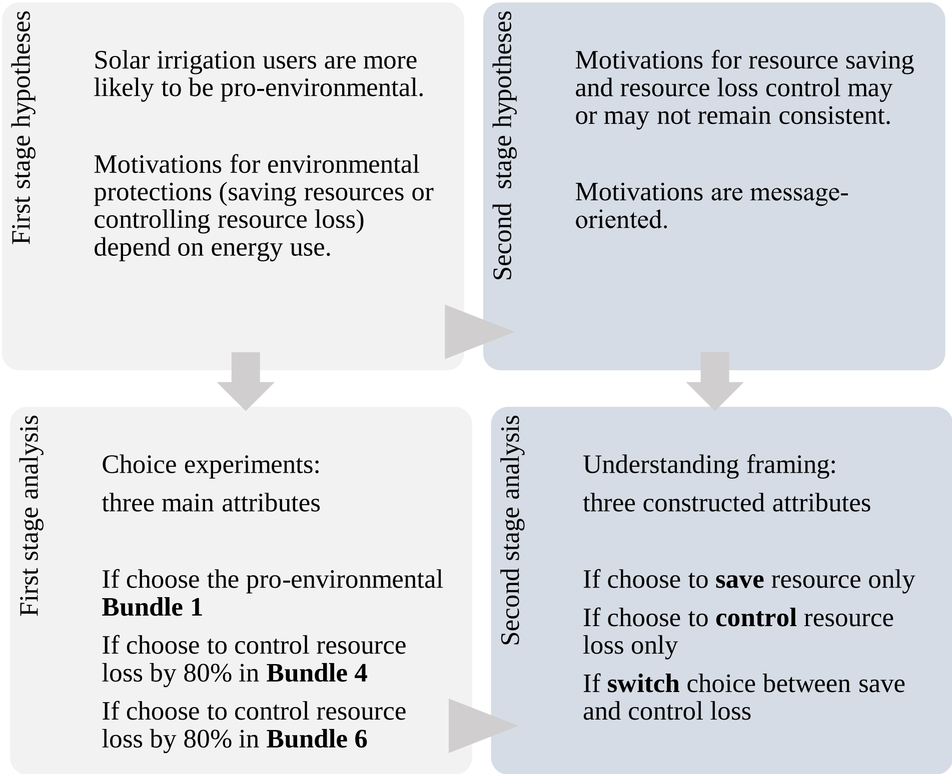


Figure 4. 4 Two analytical stages and the making of outcome variables.
Source: Author's preparation.
Note: This figure presents the analytical stages and the making of outcome variables for the analyses. The frame sets in choice experiments use and analyse the main attributes directly (light grey box). In the second stage, the levels are constructed from the second and third frame sets (bluish grey box).

4.3.2.2 Empirical strategy

The empirical strategy is to compare the outcome variables (the main attributes and the constructed frame-level attributes) for solar and non-solar users. In doing so, two probability models are used- i) the logit regression model to estimate the main binary level frame attributes, and ii) the multinomial regression model to estimate the categorical frame levels. While modelling the choices, the assumption is that farmers' selection process for solar irrigation does not consider their perceptions, preference, and sustainable actions. Thus, the probability of the outcome variables is estimated for the effects of solar irrigation, i.e., solar irrigation use and the selected farm-household covariates.

The logit regression process uses the following linear predicted model of outcome variable y_i in each frame set:

$$y_i = \alpha_0 + \alpha_1 T_i + \acute{\beta} X_i \qquad \text{Equation 4. 1}$$

This estimates the probability of making a bundle choice (i.e., the outcome variables, coded as 1 in each frame set described above). The bundle choice takes place in terms of log odds as a linear combination of the selected explanatory variables. The probability of $y_i = 1|treatment_i, X_i$ ranges between 0 and 1 and the logit function is, $p_i = \frac{1}{1+ e^{-(\alpha_0 + \alpha_1 T_i + \acute{\beta} X_i)}}$. The expression, $1 - p_i = \frac{1}{1+ e^{(\alpha_0 + \alpha_1 T_i + \acute{\beta} X_i)}}$ is the probability of $y_i = 0|treatment_i, X_i$. The estimation of the logit model gives:

$$\ln\left(\frac{p_i}{1 - p_i}\right) = \alpha_0 + \alpha_1 T_i + \acute{\beta} X_i + \epsilon_i \qquad \text{Equation 4. 2}$$

Here, $\alpha_1 = \left(\frac{\partial p_i}{\partial T_i}\right)$ estimates the probability of outcome variables that takes the value 1 if a farmer uses solar irrigation and ϵ_i is the random component. The results section reports the odds ratio, marginal effect, and margins of the explanatory variables for each outcome variable. The odds ratio for solar irrigation is the odds of choosing a bundle by a solar user relative to the same by a non-solar user. The marginal effect shows the effect magnitude of solar irrigation use on each frame choice. The margins are the average predicted probabilities of a bundle choice response at specified values of solar irrigation use, i.e., $solar = 1$ and $non - solar = 0$. Thus, the margins are the comparisons between solar and non-solar users in favour of i) pro-environmental bundle choice, ii) choosing to control energy loss by 80% and iii) choosing to control energy loss by 50%.

In the logit model, it is assumed that ε_i is an error term with a mean of 0 and a constant variance and both T_i and X_i (a set of K covariates) are independent of ε_i. The covariates are independent of solar irrigation use and $\acute{\beta}$ is a vector of K parameters and our inference object. Correlation coefficients show if there is any perfect linear relationship between the explanatory variables. The covariates include four scale variables, i.e., farmers' education, farming experience, number of farm machines owned, frequency of any partial and/or full crop loss in the past 10 years, and five binary variables, i.e., *if perceive that own irrigation energy is sustainable*, *if prefer solar over fossil energy*, *if manage crop residue sustainably*, *if manage household waste sustainably*, and *if use any sustainable agriculture*. The calculation of the descriptive statistics includes measures of the selected explanatory and outcome variables for the full sample, solar, and non-solar user groups. The descriptive table also reports means and standard deviations for the scale variables, frequency percentage of 'yes' responses for the categorical variables, and a sample *t*-test for each variable testing the difference in means between solar and non-solar user groups.

The first analytical stage compares different groups of farmers based on their perceptions, preference, and sustainable activities. Utilizing the logit models to predict the probability of making a pro-environmental choice and two types of motivations, the margins of other categorical variables are calculated. Thus it shows heterogeneity among, i) farmers who prefer solar over fossil and those who do not, ii) farmers who manage crop residue sustainably and those who do not, iii) farmers who manage household waste sustainably and those who do not, and iv) farmers who use sustainable agriculture and those who do not. The probability of making a pro-environmental bundle choice is estimated for five categories of farmers who prefer solar to fossil energy. This shows group differences in pro-environmental behaviour over various reasons behind solar preference over fossil energy. Then, the probability of pro-environmental behaviour is estimated for the effect of a high solar adoption network[10].

[10] Section 3.3 gives the details of the construction of the regional dummy variable by solar adoption network.

The prediction includes the probability of pro-environmental behaviour for high and low solar adoption areas separately.

The second stage of analysis employs multinomial logit (MNL) regression models to estimate the probabilities of the constructed motivation variable, y_i , which has three categories i.e., 'choose to save resource only', 'choose to control resource loss only' and 'choose to switch for proportions'. These attributes are the three unordered independent categories, implying that all categories are mutually exclusive (Greene, 2013; Freese and Long, 2000)[11]. The codes for the categories are arbitrary. This means that there is no ascending or descending order or value between the categories. For instance, 'choose to save resource only', coded as 1 is not less than the outcome of 'choose to control resource loss only' coded as 2, and 'choose to switch for proportions' coded as 3. A similar explanation goes for the other categories. Now in the MNL model, for the three categories, the estimates of three coefficients are, α_{11}, α_{12}, and α_{13} corresponding to each category as follows:

$$p_r(y_i = 1) = \frac{e^{(\alpha_{01}+ \alpha_{11}T_i+ \acute{\beta}X_i)}}{e^{(\alpha_{01}+ \alpha_{11}T_i+ \acute{\beta}X_i)}+ e^{(\alpha_{02}+ \alpha_{12}T_i+ \acute{\beta}X_i)+} + e^{(\alpha_{03}+ \alpha_{13}T_i+ \acute{\beta}X_i)}}$$

$$p_r(y_i = 2) = \frac{e^{(\alpha_{02}+ \alpha_{12}T_i+ \acute{\beta}X_i)}}{e^{(\alpha_{01}+ \alpha_{11}T_i+ \acute{\beta}X_i)}+ e^{(\alpha_{02}+ \alpha_{12}T_i+ \acute{\beta}X_i)+} + e^{(\alpha_{03}+ \alpha_{13}T_i+ \acute{\beta}X_i)}}$$

$$p_r(y_i = 3) = \frac{e^{(\alpha_{01}+ \alpha_{13}treatment_i+ \acute{\beta}X_i)}}{e^{(\alpha_{01}+ \alpha_{11}T_i+ \acute{\beta}X_i)}+ e^{(\alpha_{02}+ \alpha_{12}T_i+ \acute{\beta}X_i)+} + e^{(\alpha_{03}+ \alpha_{13}T_i+ \acute{\beta}X_i)}}$$

To identify the model and avoid getting the same probabilities for each category of y_i, a base category or a reference category is specified. In this case, 'choose to save resource only' is taken as the reference category to separate the effect of 'motivated

[11] One of the underlying conditions of MNL model is the condition of IIA (i.e. independence of irrelevant alternatives). We conduct Hausman test for IIA and confirm that the condition is not violated. Appendix B inludes the purpose and details of this test.

by the message' and the effect of 'motivated by volume'. Now the equations are as follows:

$$p_r(y_i = 1) = \frac{1}{1 + e^{(\alpha_{02} + \alpha_{12}T_i + \acute{\beta}X_i) +} + e^{(\alpha_{03} + \alpha_{13}T_i + \acute{\beta}X_i)}}$$

$$p_r(y_i = 2) = \frac{e^{(\alpha_{02} + \alpha_{12}T_i + \acute{\beta}X_i)}}{e^{(\alpha_{01} + \alpha_{11}T_i + \acute{\beta}X_i) +} e^{(\alpha_{02} + \alpha_{12}T_i + \acute{\beta}X_i) +} + e^{(\alpha_{03} + \alpha_{13}T_i + \acute{\beta}X_i)}}$$

$$p_r(y_i = 3) = \frac{e^{(\alpha_{02} + \alpha_{13}T_i + \acute{\beta}X_i)}}{e^{(\alpha_{01} + \alpha_{11}T_i + \acute{\beta}X_i) +} e^{(\alpha_{02} + \alpha_{12}T_i + \acute{\beta}X_i) +} + e^{(\alpha_{03} + \alpha_{13}T_i + \acute{\beta}X_i)}}$$

These equations produce relative probabilities for each category to the reference category. This is the relative risk ratio. Thus the relative risk of 'choose to control resource loss' over 'choose to save resource' is:

$$\frac{p_r(y_i = 2)}{p_r(y_i = 1)} = e^{(\alpha_{02} + \alpha_{12}T_i + \acute{\beta}X_i)}$$ Equation 4. 3

Similarly, this calculates the relative risk of 'choose to switch for proportions' over 'choose to save resource' as:

$$\frac{p_r(y_i = 3)}{p_r(y_i = 1)} = e^{(\alpha_{03} + \alpha_{13}T_i + \acute{\beta}X_i)}$$ Equation 4. 4

The realtive risk ratio greater than 1 will explain that the event if more likely to happen and vice versa. The covariates X_i include farmers' education, farming experience, number of farm machines owned, if they experienced any partial and/or full crop loss in the past 10 years, if they manage crop residue sustainably, if they manage household waste sustainably, and if they use any sustainable agriculture. The estimation procedure is applied to the full sample and then high and low solar adoption areas separately. Separate MNL regression models are estimated for the framing categories, controlling for the effect of actual reasons behind solar irrigation. These models are for solar users only. This study observed nine reasons behind solar irrigation use, namely- i) less labor cost, ii) less chemical inputs, iii) low irrigation cost, iv) increase in crop quantity, v) time-saving and less system pressure, vi) no installation personally, vii) environmentally safe, viii) no harm to human health, ix) less water pollution, and x) better crop health. These reasons are reduced into three categories, i.e., use solar for economic efficiency (combining points, i-iv), use solar for environmental sustainability (combining points, vii-x), and use solar for easy management (combining points, v-vi). The relative risk coefficients of these three reasons are calculated for the constructed environmental motivations.

4.3.3 Descriptive statistics and sample balancing tests

This section first shows sample descriptions of farming experience, farmers' education level, number of farm machines in possession, crop loss experience, sustainability perception of energy that farmers use, their preference for solar and fossil energy, on-farm crop residue management, off-farm household waste management, their sustainable on-farm activities, and finally their choices in three experiments. Solar and non-solar using farmers are similar in experiencing any partial or complete crop loss, and in sustainably managing crop residues and household waste. This indicates that groups do not differ in sustainable off-farm and post-harvest on-farm actions and experience. However, they differ in schooling years, possession of farm machinery, crop loss frequency, sustainability perception of energy farmers use, their preference for solar and fossil energy, and sustainable pre-harvest on-farm activities. Therefore, groups differ in human capital, and technology-choice and -use.

Table 4. 1 Descriptive statistics of the explanatory and environmental outcome variables.

Sl. No.	Variables	Full Sample Mean/ frequency	Solar adopters Mean/ frequency	Non-solar adopters Mean/ frequency	*p*-value of difference
A.	**Explanatory variables**				
1.	Farming experience (years)	26.16	25.14	27.17	0.0307
2.	Farmer's education (schooling years)	4.72	5.15	4.29	0.0183
3.	Farm machinery in possession (number)	0.44	0.35	0.55	0.0004
4	If experience any crop loss	91.50% (yes)	90.50% (yes)	92.50% (yes)	0.3111
4.	Experience of crop loss (times)	2.39	2.28	2.51	0.0238
5.	If perceive that own irrigation energy is sustainable (1= yes, 0= no)	66.62% (yes)	92.50% (yes)	40.75% (yes)	0.0000
6.	If prefer solar over fossil energy (1= yes, 0= no)	76.13% (yes)	89% (yes)	63.25% (yes)	0.0000
7.	If managing crop residue sustainably (1= yes, 0= no)	91.38% (yes)	91.50% (yes)	91.25% (yes)	0.8999
8.	If managing waste sustainably (1= yes, 0= no)	95.88% (yes)	95.50% (yes)	96.25% (yes)	0.5943
9.	If using any of the sustainable farming practices (1= yes, 0= no)	95.75% (yes)	99.25% (yes)	92.25% (yes)	0.0000
B.	**Choice experiments**				
10.	If choose a pro-environmental bundle (1= yes, 0= otherwise)	71.63% (yes)	81.25% (yes)	62.00% (yes)	0.0000
11.	If choose to control resource loss by 80% (1= yes, 0= otherwise/save)	68.13% (yes)	68.50% (yes)	67.75% (yes)	0.8202
12.	If choose to control resource loss by 50% (1= yes, 0= otherwise/save)	59.63% (yes)	60.25% (yes)	59.00% (yes)	0.7190
C.	**Understanding framing**				
13.	If choose to save resource	29.50% (yes)	28.25% (yes)	30.75% (yes)	0.4388
14.	If choose to control resource loss	57.25% (yes)	57% (yes)	57.50% (yes)	0.8865
15.	If switch choice for proportions	13.25% (yes)	14.75% (yes)	11.75% (yes)	0.2113

Source: Author's calculation.

Note: This table reports the descriptive statistics of the selected explanatory/sample balancing variables (1-9) and the outcome variables (10-15) (also see Figure 4.6). The *p*-value in the last column suggests the significance in the mean difference for each variable between solar and non-solar irrigation user-farmers. Percentage frequencies of "yes" are reported for the discrete binary variables and means are reported for the scale variables. The sustainable crop residue management combines the categories- 'decompose', 'sell', 'cooking fuel', and 'animal fodder'. The sustainable waste management combines the categories- 'dispose correctly', 'reuse/recycle/sell' and 'decompose'. A correlation table is also prepared (Figure 4.5) in order to check multicollinearity between the selected explanatory variables.

The average farming experience is approximately 26 years and non-solar users have a longer experience. Farmers in the study area have not even completed primary education. Solar and non-solar users differ in education attainment level (at the 5% level). Solar users have a higher level of education than non-solar users. Solar users' farm machinery possession is lower than that of non-solar users (significant difference at the 1% level). More than 90% of the farmers experienced either partial or full crop loss in the past 10 years. Solar farmers less frequently suffered from any crop loss than non-solar farmers did. Solar users have significantly a higher (92.50% versus 40.75%) understanding of their energy being sustainable, and a larger preference for solar over fossil energy (89% versus 63.25%). Using any type of on-farm sustainable activity (e.g., water-efficient irrigation, organic fertilizer, renewable irrigation, controlled tillage, and so on) is considerably high in the study area (99%). In the case of outcome variables in three choice experiments, it appears that solar users tend to be pro-environmental. However, motivations do not vary between solar and non-solar users irrespective of motivation type, i.e., between surely saving resources and possibly controlling resource losses. Groups do not differ in any of the framing effect outcomes. Even in switching proportions, there is no difference between solar and non-solar users, indicating no effect of message contents.

if uses solar irrigation									
-0.076	farming experience								
0.083	-0.355	farmer's schooling years							
-0.125	-0.031	0.052	own farm-machinery						
-0.080	0.053	0.019	-0.038	crop loss frequency					
0.549	-0.092	0.036	-0.135	-0.097	if used energy perceived as sustainable				
0.302	-0.029	0.025	0.013	0.069	0.082	prefer solar			
0.004	-0.025	-0.049	0.055	-0.002	-0.076	0.047	if manage crop residue sustainably		
-0.019	-0.036	0.036	0.045	-0.022	-0.054	0.046	0.115	if manage household waste sustainably	
0.174	-0.102	-0.009	-0.006	-0.055	0.074	0.086	0.156	0.268	if use any sustainable farming practice

Figure 4. 5 The correlation table for the selected explanatory variables for pro-environmental choice.
Source: Authors' preparation.
Note: This figure shows that there is no perfect collinearity between the selected explanatory variables. Two separate colours indicate positive (bluish grey) and negative (whitish grey) correlations between variables.

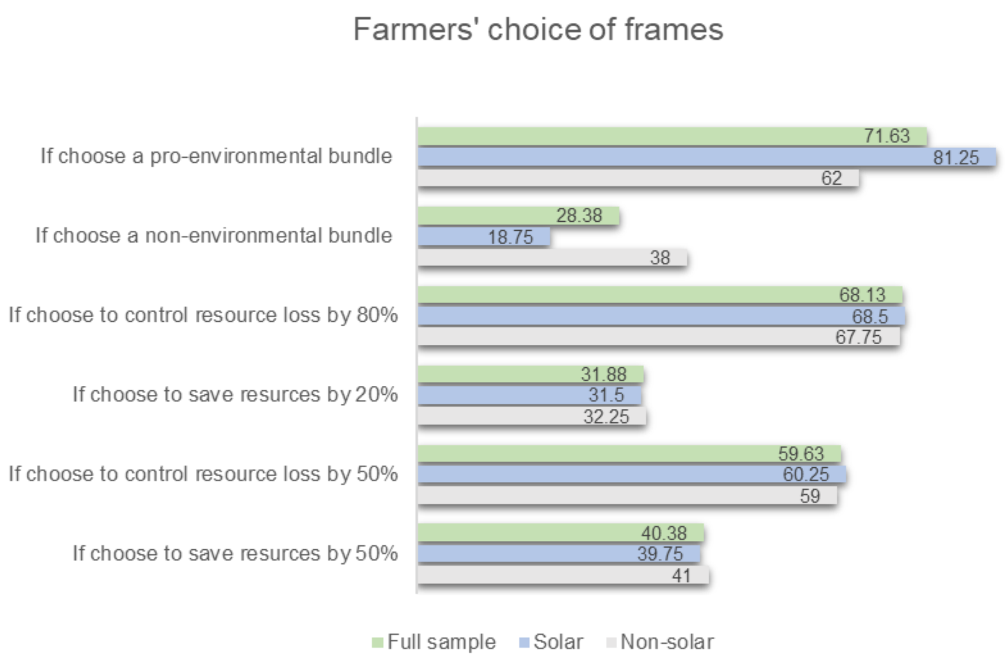


Figure 4. 6 Frequency distributions of farmers' stated choice of frames.
Source: Authors' preparation.
Note: This figure presents the percentage distributions of the three main attributes frame choices. The proportions are for the full sample (lime green bars), solar users (light blue bars) and non-solar users (light grey bars). All description statistics are frequency percentages.

4.4 Results and discussions

4.4.1 What impacts farmers' pro-environmental behaviour

Farmers' irrigation energy choice has a significant impact on their stated pro-environmental choice of bundle. The results of Model 4.1.a (Table 4.2) show that the odds of solar users choosing the pro-environmental bundle are 3.18 times higher than that of the same of non-solar users. In terms of marginal effects, if farmers use solar irrigation, they are 22.34 percentage points more likely to make a pro-environmental choice. Farmer's experience, schooling years, and ownership of farm machinery are the determining factors for making such a choice. The pro-environmental tendency is higher among less experienced farmers and if farmers do not perceive their irrigation energy as a sustainable one. Pro-environmental choice-making probability is high for households managing wastes sustainably (risk ratio, 0.1635 significant at the 10% level in Table 4.5). On-farm sustainable practices, solar preference over fossil, and sustainable crop residue management have no impact on such choice-making. Both sustainable practices and solar preference are perception-based indicators. Considering the average education level, it is possible that farmers are not capable of making a normative evaluation of their agricultural practices.

These results also suggest that farmers' pro-environmental behaviour is more action-oriented than perception-based. Actions include both on-farm (i.e., irrigation energy) and off-farm (i.e., household waste management) behaviour. In addition, education, crop residue management, and sustainable practices positively impact farmers' behaviour. These results indicate that technology use may influence behaviour through sustainable activities. Solar users living in high and low adoption areas are more likely to choose a pro-environmental bundle (Table 4.2). The difference in the marginal effects is negligible (2 percentage points). Predicted probability appears to be volatile while controlled for high and low adoption areas separately (Figure B.3). Young farmers are pro-environmental in low adoption areas while education prompts pro-environmental behaviour in high adoption areas. Crop residue management stimulates pro-environmental behaviour in high adoption areas and waste management improves it in low adoption areas. Sustainability perception about irrigation and own farming practice also varies with solar adoption intensity. Farmers choosing a pro-environmental bundle in high adoption areas have a higher sustainability perception of their farming practice. This study separately estimates group-wise pro-environmental behaviour of those who prefer solar to fossil energy for various reasons (Table 4.3). Statistically, significant differences are observed between solar and non-solar users who perceived that 'fossil burn increases environmental damages' (the difference is 0.1901 at the 1% significance level) and 'solar does not harm the environment' (the difference is 0.1269 at the 5% significance level). Solar pro-environmental farmers retain a stronger perception of these matters. (Figure 4.8). Other perceptions, for example, 'solar energy is not wasteful', 'the next generation will not face any energy shortage', and 'solar ensures efficient water use' have no impact on the two groups and hence energy use.

Table 4. 2 The estimated probability of pro-environmental behaviour.

	If choose a pro-environmental bundle (1) and otherwise non-environmental (0)					
	Model 4.1.a Full sample		Model 4.1.b High adoption areas		Model 4.1.c Low adoption areas	
Variables	Odds ratio	Marginal effect	Odds ratio	Marginal effect	Odds ratio	Marginal effect
If use solar irrigation	3.1888***	0.2234***	3.5876***	0.2358***	3.4064***	0.2199***
	(0.6720)	(0.0391)	(1.0765)	(0.0529)	(1.0850)	(0.0540)
Farming experience	0.9859**	-0.0027**	0.9857	-0.0026	0.9791**	-0.0038**
	(0.0066)	(0.0013)	(0.0097)	(0.0017)	(0.0095)	(0.0017)
Farmer's education	1.0324*	0.0062*	1.0636**	0.0110***	1.0027	0.0005
	(0.0185)	(0.0034)	(0.0258)	(0.0042)	(0.0287)	(0.0051)
Own farm machinery	1.3001**	0.0510**	1.1918	0.0314	1.5740**	0.0810**
	(0.1531)	(0.0227)	(0.1939)	(0.0290)	(0.3091)	(0.0345)
Experience of crop loss	1.0054	0.0010	1.0304	0.0054	1.0310	0.0055
	(0.0582)	(0.0113)	(0.0775)	(0.0134)	(0.1016)	(0.0176)
If perceive that own irrigation	0.6459**	-0.0820**	0.7955	-0.0402	0.4886**	-0.1212**
energy is sustainable	(0.1329)	(0.0372)	(0.2237)	(0.0485)	(0.1547)	(0.0498)
If prefer solar over fossil energy	1.1219	0.0226	1.2123	0.0351	0.9230	-0.0142
	(0.2213)	(0.0394)	(0.3321)	(0.0508)	(0.2821)	(0.0534)
If managing crop residue	1.5152	0.0869	2.7444***	0.1990***	0.7833	-0.0416
sustainably	(0.4314)	(0.0634)	(1.0081)	(0.0752)	(0.3908)	(0.0809)
If managing waste sustainably	2.2173**	0.1773*	2.2003	0.1545	2.8438**	0.2172*
	.8869)	(0.0974)	(1.4034)	(0.1324)	(1.5084)	(0.1195)
If using any of the sustainable	1.9700*	0.1487	5.2812***	0.3433***	1.0387	0.0068
farming practices	(0.7851)	(0.0955)	(3.2679)	(0.1263)	(0.6350)	(0.1108)
Observations	800		414		386	
Log likelihood	-438.37		-221.51		-207.22	
Prob > chi2	0.0000		0.0000		0.0002	

Source: Author's calculation.

Note: This table reports the logit (Equation 4. 1) regression results of the probability of choosing a pro-environmental bundle for the full sample, and high and low adoption areas. Both odds ratios and marginal effects are reported here. Section 4.1 presents the discussion and interpretations the results. The predictive strengths of these models are visualized in ROC analysis, and sensitivity and specificity of the models (Figure B.1 in Appendix B). These logits models also produce margins of various groups for the binary variables (Table 4.5). Finally, the standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4. 3 Probability of a pro-environmental bundle choice between farmers who prefer solar over fossil energy for various reasons.

	Pro-environmental behaviour: when perception is explicit		
	Solar	Non-solar	Difference
Model 4.2.a	0.8412	0.6510	0.1901***
Farmer perceiving **fossil burn increases environmental damage**	(0.0224)	(0.0415)	(0.0526)
Sample size		530	
Prob > chi2		0.0000	
Log likelihood		-270.12622	
Model 4.2.b	0.8129	0.7381	0.0748
Farmer perceiving **energy is not wasted**	(0.0280)	(0.0439)	(0.0593)
Sample size		407	
Prob > chi2		0.0096	
Log likelihood		-201.59503	
Model 4.2.c	0.8008	0.8112	-0.0103
Farmer perceiving **the next generation will not face any energy shortage**	(0.0361)	(0.0479)	(0.0731)
Sample size		359	
Prob > chi2		0.0681	
Log likelihood		-171.25191	
Model 4.2.d	0.7584	0.7090	0.0493
Farmer perceiving **solar ensures efficient water use**	(0.0341)	(0.0481)	(0.0592)
Sample size		239	
Prob > chi2		0.0793	
Log likelihood		-132.63427	
Model 4.2.e	0.8268	0.6999	0.1269**
Farmer perceiving **solar does not harm the environment**	(0.0275)	(0.0429)	(0.0576)
Sample size		414	
Prob > chi2		0.0013	
Log likelihood		-208.15554	

Source: Author's calculation.

Note: This table presents the margins of the various reasons for solar preference over fossil energy to predict the probability of choosing a pro-environmental bundle. Categories are created by an interaction term of two dummy variables, i.e., (being a solar/non-solar user)*(reason for solar preference). The block letters highlight these reasons. Solar and non-solar farmers significantly differ in Model 4.2.a and Model 4.2.e (visualized in Figure 4.8). Appendix B presents the ROC analysis of the models (Figure B.2). The standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4. 4 The estimated pro-environmental motivations.

	If choose to control resource loss by 80%				If choose to control resource loss by 50%	
	Model 4.3.a		Model 4.3.b		Model 4.4	
Variables	Odds ratios	Marginal effects	Odds ratios	Marginal effects	Odds ratios	Marginal effects
If use solar irrigation	1.0139 (0.2002)	0.0030 (0.0425)	--	--	1.0182 (0.1514)	0.0043 (0.0357)
If use solar irrigation and live in high adoption areas	--	--	1.4632* (0.2885)	0.0784** (0.0389)	--	--
Farming experience	0.9907 (0.0062)	0.0020 (0.0013)	0.9887* (0.0062)	-0.0024* (0.0014)	--	
Farmer's education	1.0553*** (0.0177)	0.0116*** (0.0036)	1.0455*** (0.0177)	0.0095*** (0.0036)	1.0248* (0.0147)	0.0059* (0.0035)
Own farm machinery	1.0172 (0.1009)	0.0037 (0.0213)	0.9693 (0.0977)	-0.0067 (0.0216)	1.0146 (0.0953)	0.0035 (0.0226)
Experience of crop loss	1.0048 (0.0548)	0.0010 (0.0117)	1.0081 (0.0557)	0.0017 (0.0118)	1.0324 (0.0535)	0.0077 (0.0125)
If perceive that own irrigation energy is sustainable	1.0909 (0.2173)	0.0188 (0.0433)	1.0048 (0.1755)	0.0010 (0.0374)	--	--
If prefer solar over fossil energy	0.8491 (0.1647)	0.0346 (0.0403)	0.7919 (0.1492)	-0.0487 (0.0383)	--	--
If managing crop residue sustainably	1.6078* (0.4340)	0.1085* (0.0646)	1.8021** (0.4961)	0.1357** (0.0667)	1.8469** (0.4765)	0.1514** (0.0638)
If managing waste sustainably	1.3045 (0.5134)	0.0596 (0.0914)	1.4995 (0.6011)	0.0921 (0.0956)	1.5017 (0.5461)	0.1002 (0.0908)
If using any of the sustainable farming practices (perceived)	0.5106 (0.2278)	-0.1260* (0.0706)	0.4092** (0.1848)	-0.1579** (0.0623)	--	--
If receive any agricultural training	--	--	1.7226** (0.3817)	0.1081*** (0.0404)	1.4655* (0.2920)	0.0892* (0.0449)
Observations	800		800		800	
Log likelihood	-488.82		-483.68		-532.13	
Prob > chi2	0.0080		0.0003		0.0367	

Source: Author's calculation.

Note: This table reports the logit (Equation 4. 1) regression results of the choice of controlling resource loss by 80% and the choice of controlling resource loss by 50%. Both odds ratios and marginal effects are reported here. Section 4.1 presents the discussion and interpretations the results. Model 4.3 does not include all the explanatory variables of the two other models because of a better model fit. For similar reasons, I have used full sample only instead of observations in high and low adoption areas separately. However, for sensitivity, Model 4.2.b includes a dummy variable for solar users living in high adoption areas. The predictive strengths of these models are visualized in ROC analysis, and sensitivity and specificity of the models (Figure B.1 in Appendix B). These logits models also produce margins of various groups for the binary variables (Table 4.5). Finally, the standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4. 5 Group heterogeneity in pro-environmental behaviour and motivations.

Outcome variables	Farmers' categories and difference between categories		
	Solar adopters	**Non-solar adopters**	**Difference**
Pro-environmental bundle choice	0.8203	0.6034	0.2169***
	(0.0201)	(0.0281)	(0.0378)
If choose to control resource loss by 80%	0.6827	0.6797	0.0029
	(0.0263)	(0.0264)	(0.0416)
If choose to control resource loss by 50%	0.5983	0.5941	0.0042
	(0.0245)	(0.0245)	(0.0351)
Outcomes: Action-oriented	**Manage crop residue sustainably**	**Do not manage crop residue sustainably**	**Difference**
Pro-environmental bundle choice	0.7233	0.6422	0.0810
	(0.0158)	(0.0560)	(0.0584)
If choose to control resource loss by 80%	0.6901	0.5841	0.1060*
	(0.0168)	(0.0602)	(0.0627)
If choose to control resource loss by 50%	0.6091	0.4594	0.1496**
	(.0179)	(0.0602)	(0.0631)
	Manage waste sustainably	**Do not manage waste sustainably**	**Difference**
Pro-environmental bundle choice	0.7229	0.5594	0.1635*
	(0.0154)	(0.0866)	(0.0882)
If choose to control resource loss by 80%	0.6836	0.6253	0.0582
	(0.0165)	(0.0871)	(0.0890)
If choose to control resource loss by 50%	0.6003	0.5017	0.0985
	(0.0175)	(0.0874)	(0.0892)
Outcomes: Perception-based	**Prefer solar irrigation**	**Do not prefer solar irrigation**	**Difference**
Pro-environmental bundle choice	0.7219	0.7005	0.0213
	(0.0179)	(0.0315)	(0.0371)
If choose to control resource loss by 80%	0.6730	0.7071	-0.0339
	(0.0190)	(0.0338)	(0.0396)
	Use any sustainable agriculture (SA)	**Do not use any sustainable agriculture (SA)**	**Difference**
Pro-environmental bundle choice	0.7225	0.5844	0.1380
	(0.0155)	(0.0857)	(0.0875)
If choose to control resource loss by 80%	0.6755	0.8004	-0.1249*
	(0.0167)	(0.0681)	(0.0707)
	If own used energy is sustainable	**If own used energy is not sustainable**	**Difference**
Pro-environmental bundle choice	0.6852	0.7628	-0.0775**
	(0.0214)	(0.0245)	(0.0351)
If choose to control resource loss by 80%	0.6873	0.6689	0.0184
	(0.0213)	(0.0328)	(0.0423)

Source: Author's calculation.

Note: This table reports the produced margins for various categories of farmers and the differences between these categories. Figure 4.8 visualizes the category-wise margins that have significant differential impacts on the respective outcome variables. The standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

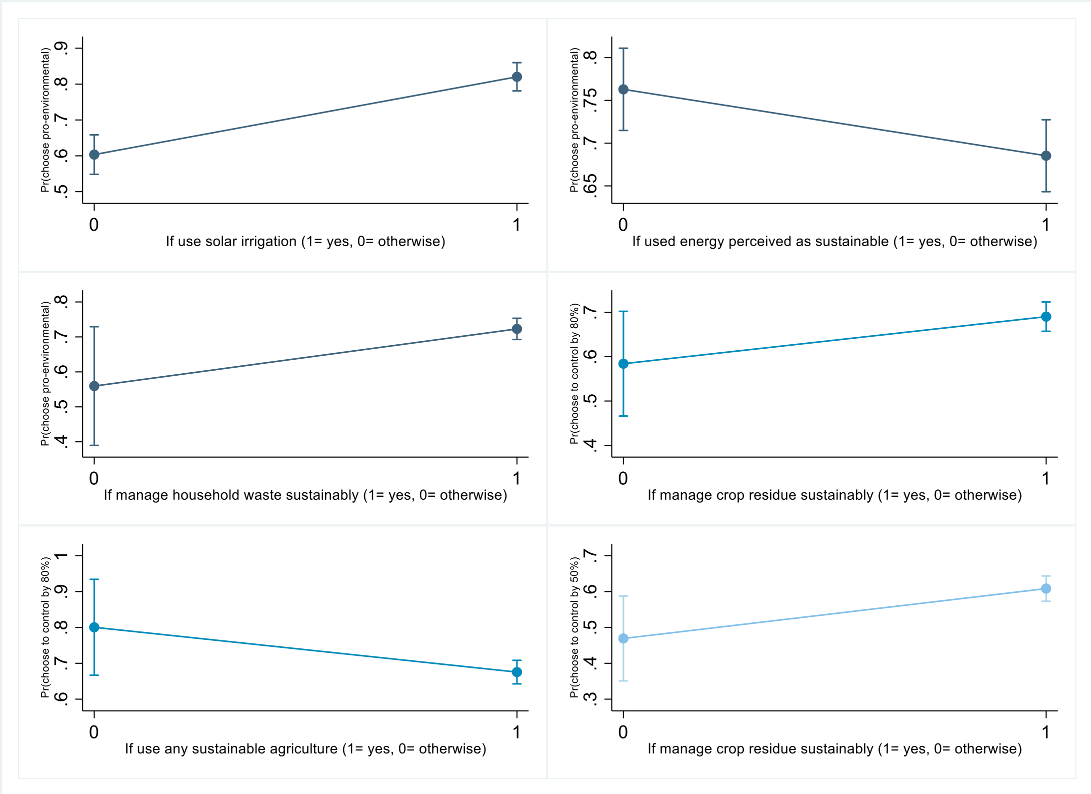


Figure 4. 7 Margins of the binary variables significantly influencing the three attributes.
Source: Author's preparation.
Note: This figure depicts the margins of the binary variables that are significantly different in various categories. This figure is produced from the estimated results of Model 4.1.a, 4.3.a and 4.4. Separate colours are used for the three predicted probabilities of choices, i.e., dark blue for the predicted values of pro-environmental bundle (Model 4.1.a), bright blue for the predicted values of choosing resource loss control by 80% (Model 4.3.a) and light blue for the same of choosing resource loss control by 50% (Model 4.4).

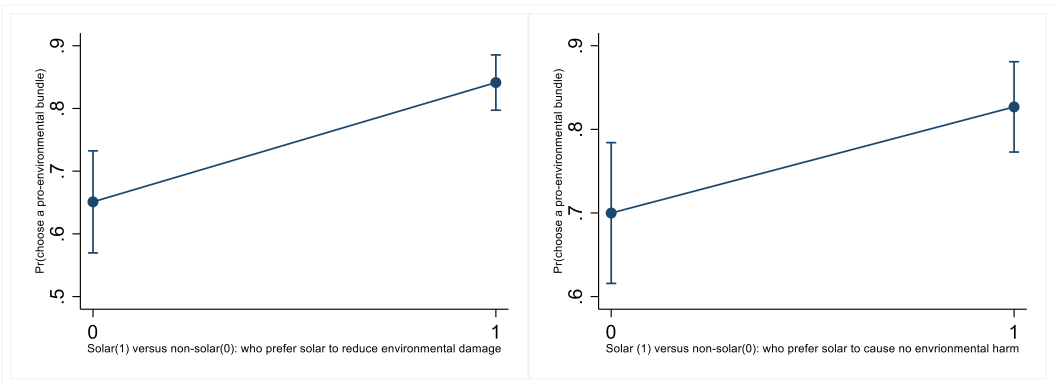


Figure 4. 8 Margins of the reasons for solar preference influencing a pro-environmental bundle choice.
Source: Author's preparation.
Note: This figure depicts the margins that are significantly different in two categories for solar and non-solar users who prefer solar over fossil energy. This figure is produced from the estimated results of Model 4.2.a., and 4.2.e.

4.4.2 What affects environmental motivations

The estimated choices in frame-set two and three show that energy use does not explain any category of environmental motivations. I do not observe any impact of solar use on the choice of resource loss control, with either 80% or 50% possibilities. However, if solar users are in high adoption areas, they tend to prefer 80% loss control of resources (Odds ratio 1.46 at the 10% significance level). Farmers with an additional schooling year tend to prefer resource loss control by 80% (odds ratio, 1.05) and the same by 50% (odds ratio 1.02). Young farmers are more likely to make a similar choice when controlled for solar use in high adoption areas (Model 4.3.b). Farmers managing crop residues sustainably tend to choose resource loss control in both frames. There is a significant group difference between farmers managing crop residue sustainably and those who do not (0.1060 for the 80% and 0.1496 for the 50% frames presented in Table 4.5). Sustainable (as perceived by farmers) practice adopters are less likely to make the loss control choice in frame-set two, i.e., they are more likely to choose to save energy (by 12.60 percentage points). Farmers receiving any agricultural training tend to prefer resource loss control in both cases, i.e., 80% and 50% possibilities. However, the impact of training, in this case, remains ambiguous as the content of the training is not observed. Overall, the environmental motivations of farmers in the study area are more oriented toward resource loss control. Previous inefficient use of resources and the relevant primary concern may have caused such motivation. Thus, between frame sets two and three, message contents may or may not influence their motivations. Therefore, measuring the consistency of motivations could show the significance of messages.

4.4.3 Consistency of motivations

The results of the MNL regression models allowed to evaluate the consistency of environmental motivations (Table 4.6). Energy use does not explain if farmers tend to control resource loss (i.e., no energy use impact on consistent motivations) relative to the resource-saving choice. Relative to the same base category, there is no impact of energy use on switching preference due to proportions (i.e., 20%-80% or 50%-50%) or the wording of messages (i.e., surety versus possibility). These imply that motivations for saving and/or controlling the loss of resources are not sensitive to messages or any frame contents, hence, there is no framing effect. Such findings of ambiguous framing effects are consistent with some recent evidence (e.g., Derecskei and Csongrádi, 2022; Korn et al., 2019; Reinhardt and Rossmann, 2021). However, there is evidence of strong impacts of loss aversion messages on pro-environmental behaviour (e.g., Grazzini et al., 2018). Probabilities of consistency and variations in choices increase with an additional schooling year (at the 1% significance level) and one time less frequent crop loss (at the 5% significance level). Crop residue management increases the probability of choice-making consistency, while sustainable practice(s) influence(s) only the switching tendency (negatively). This implies that farmers with sustainability perceptions can be sensitive to the message contents. This bears significant implications for awareness campaigns. Sustainability-focused messages in such campaigns could be more appealing if local resource conditions are emphasized. Training stimulates both consistency and switching of the stated preferences, indicating an influence of human resource development. I also observe the robustness of solar users' motivations objectively, i.e., controlled for the three reasons behind their solar irrigation choice. (Table 4.7). Farmers who use solar irrigation for economic efficiency, tend to switch choices between saving and loss control (margins, 0.13 at the 1% significance level). Solar users remain consistent about saving resources if they started using solar irrigation for environmental sustainability and easy irrigation management (significant both at the 10% level). However, none of these three variables could explain solar users' consistent choice of controlling resource loss.

Regarding environmental behaviour, *perceived self-efficacy* stimulates choices demonstrating losses (Grazzini et al, 2018) and such self-efficacy is constructed by subjective experience and actions (Bandura, 1986). Thus, farmers' pro-environmental choices and motivations may be sensitive to the efficiency of irrigation technology. To check that I estimate irrigation frequency and time[12] on solar users being pro-environmental and either saving or loss control motivated. Both solar pro-environmental users and resource control choosers use less (significant at the 1% level) irrigation both in terms of frequency and time (Table B.2). The framing of choices shows variations in energy use and irrigation behaviour. Solar pro-environmental farmers use 4 less irrigations and farmers choosing loss control by 80% use 3 less irrigations compared to others. The effect of timing is higher among solar pro-environmental users (0.8681 hours less) than among other groups (0.68 hours less for 80% loss control choosers and 0.61 hours less for 50% loss control choosers). There is no impact of irrigation frequency for solar users choosing resource control loss by 50%. However, this group uses less time for irrigation.

[12] Irrigation frequency is the mean annual irrigation days for all crops and irrigation time is the mean annual irrigation hours for all crops. Chapter 5 includes a detailed description of the measurements of the outcome variables and group differences.

Table 4. 6 Multinomial logit regression results for the categories of framing effects in bundle choices.

Variables ('If choose to save resource' is the reference category)	Model 4.5	
	If choose to control resource loss	If switch choice for proportions
	Relative risk ratio	Relative risk ratio
If a solar user	1.0151 (0.1711)	1.2820 (0.3210)
Farming experience	0.9881* (0.0065)	0.9850 (0.0096)
Farmer's education	1.0468** (0.0189)	1.0908*** (0.0270
Own farm machinery	0.9852 (0.1086)	0.9651 (0.1492)
If experience crop loss	0.4961** (0.1693)	0.3636** (0.1556)
If managing crop residue sustainably	1.9746** (0.5768)	1.2758 (0.5021)
If managing waste sustainably	1.6286 (0.6854)	1.4685 (0.8742)
If using sustainable agriculture (perceived)	0.4799 (0.2273)	0.2739** (0.1637)
If receive any agricultural training	1.8497** (0.4405)	1.9918** (0.6398)
Prob > chi2	0.0001	
Log likelihood	-732.21	

Source: Author's calculation.
Note: This table presents the multinomial logit (Equation 4. 3 and Equation 4. 4) regression results of the probability of making energy saving and/or loss control choices. The IIA test results (0.896 for category 1, 0.707 for category 2 and 0.843 for category 3) show that Prob > chi2 is greater than 0, implying all three categories are independent. The model uses the first outcome as the reference category. However, predictive margins are calculated for all thee outcomes. While this table reports the relative risk ratios, Figure B.4 (Appendix B) show the variations of effects between the three predictive margins. The standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4. 7 Multinomial logit regression results of the framing effect categories for solar users.

Variables	Outcomes		
	If choose to save resource Margins	If choose to control resource loss Margins	If choose to switch for proportions Margins
Model 4.6			
Farmers use solar energy for economic efficiency	-0.0152 (.1107)	-0.1147 (.1140)	0.1300*** (0.0344)
Controlled for explanatory variables	Yes	Yes	Yes
Observations		400	
Prob > chi2		0.0005	
Log likelihood		-363.288	
Model 4.7			
Farmers use solar energy for environmental sustainability	-0.1301 *(.0713)	0.0626 (.0740)	0.0675 (.0411)
Controlled for explanatory variables	Yes	Yes	Yes
Observations		400	
Prob > chi2		0.0005	
Log likelihood		-363.33025	
Model 4.8			
Farmers use solar energy for easy management	-0.0858* (.0515)	0.0504 (.0552)	0.0353 (.0371)
Controlled for explanatory variables	Yes	Yes	Yes
Observations		400	
Prob > chi2		0.0009	
Log likelihood		-364.13475	

Source: Author's calculation.
Note: This table presents the multinomial logit (Equation 4. 3 and Equation 4. 4) regression results of the probability of solar users (only) making resource saving and/or loss control choices. The models use the first outcome as the reference category. Solar users are categorized into three groups, i.e., farmers who use solar for economic efficiency, farmers who use solar for the environment and farmers who use solar for an easy management. Figure B.5 (Appendix B) show the variations of effects between the outcomes and solar user-groups. The standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

4.4.5 Experimental validity

For the experimental validity, I first explain the orientation of frame sets and then I evaluate the explanatory powers of the predictors and the robustness of this analysis. Müller and Rabbitt (1989) demonstrated two types of orientations in visual experiments, *reflexive* and *voluntary*; the former uses automaticity and the latter uses controlled characters. The authors argued that both orientations have some influence on each other based on hints and they differ depending on the hints presented. In reflexive visualizations, subjects are given superficial hints and in voluntary cases, logic and reasoning are presented. In a recent experiment with message orientation, showed that a sustainable diet choice relies upon the content (Rosenfeld et al., 2022). However, in their experiment, messages (i.e., menu names) used popular sustainability genre phrases that could be a source of bias. In this study, I use reflexive tools for the first frame set and voluntary for the second and the third sets. Orientations cannot interfere in the sense that farmers do not receive any hint about the frame sets. In addition, messages in the second and third frame sets are not persuasive. In this study, energy use could not explain motivations' variations and their robustness, perhaps because of the absence of a reference category in these frames. Non-environmental and/or indifferent items and/or messages could produce biased visual choices. I did not include any reference category to avoid such biases. For external validity, this study uses a farming population that is diverse across solar network intensity, i.e., low and high and across various climatic and agro-ecological zones in Bangladesh. A large sample size of 800 farming households in 12 districts thus gives sufficient representation power. Margin analysis of various cohorts regarding sustainability actions and perceptions gives additional insights into the main findings. I also compare results by solar network and then compare models by controlling the area dummy variable in four different models. I also check the choice sensitivities on irrigation profiles.

4.5 Conclusion

This study evaluates farmers' pro-environmental behaviour and motivations for irrigation energy users. I employ an inverse or competing framing approach and follow the comparative empirical strategy. I construct the pro-environmental versus non-environmental frames with items only and motivational frame sets with both items and messages. Both descriptive statistics and inferences show that solar farmers make pro-environmental choices. Being pro-environmental, the odds of solar use are 3.18 times more than that of non-solar users. Farmers in high solar network areas are more pro-environmental. However, energy use did not explain variations in motivations or the framing effect. Framing remains ambiguous in explaining the consistency and variations of motivations.

The findings of this study convey some important behavioural implications for solar network extension. I observed that pro-environmental behaviour is more action-oriented and results are robust enough to the effect of solar networks. This suggests that technology use connects both on-farm and off-farm perception and action-behaviour and this pathway improves with renewable technology adoption. Therefore, instead of voluntary off-farm sustainable activities, institutions should deliberately include such activities in their solar promotion projects. Such a policy should sway other CSA practices as well. I also observe solar farmers' pro-environmental behaviour regarding fossil-led environmental damage and the worth of solar energy for no environmental harm. Such understandings could be strong environmental nudges from peers and institutions for solar adoption.

Appendix B
Additional graphs and tables for pro-environmental behaviour

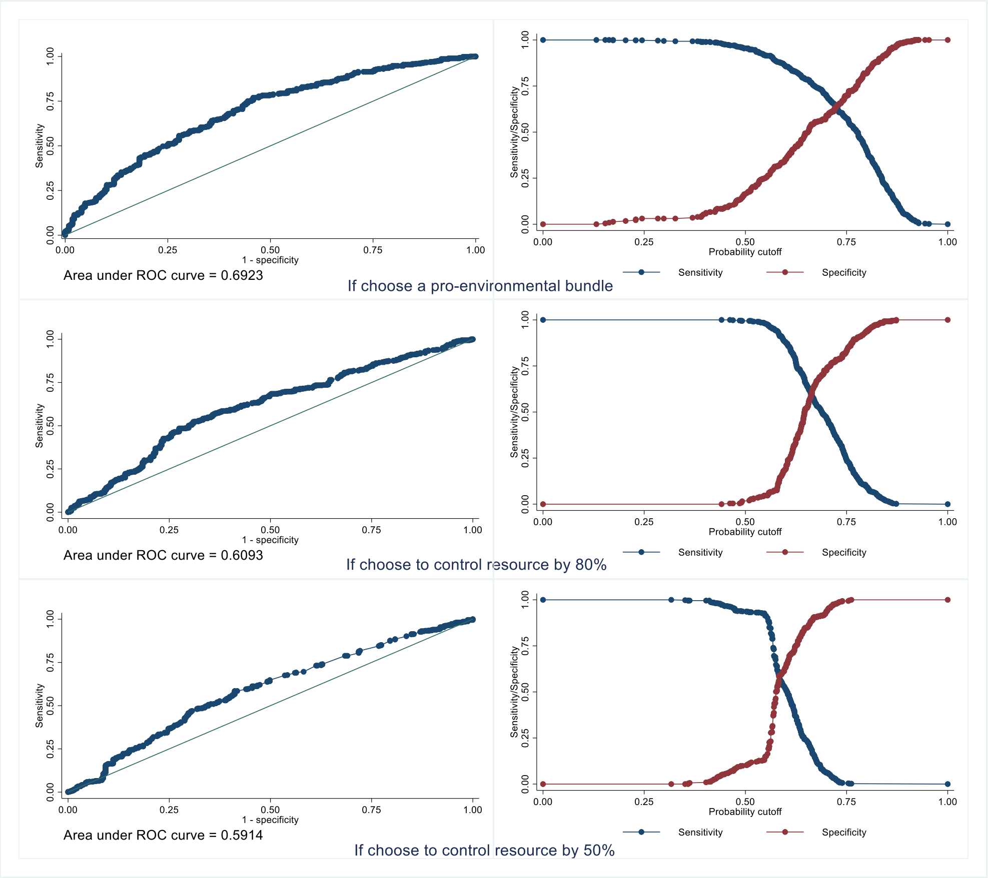


Figure B. 1 ROC analyses of Model 4.1.a, Model 4.3.a and Model 4.4.
Source: Author's preparation.
Note: This figure depicts the post estimation ROC analyses of the three logit models, Model 4.1.a, Model 4.3.a and Model 4.4. Regarding the ROC comparisons, the first model, Model 4.1.a has the highest credibility in estimating the probability of choosing a pro-environmental bundle.

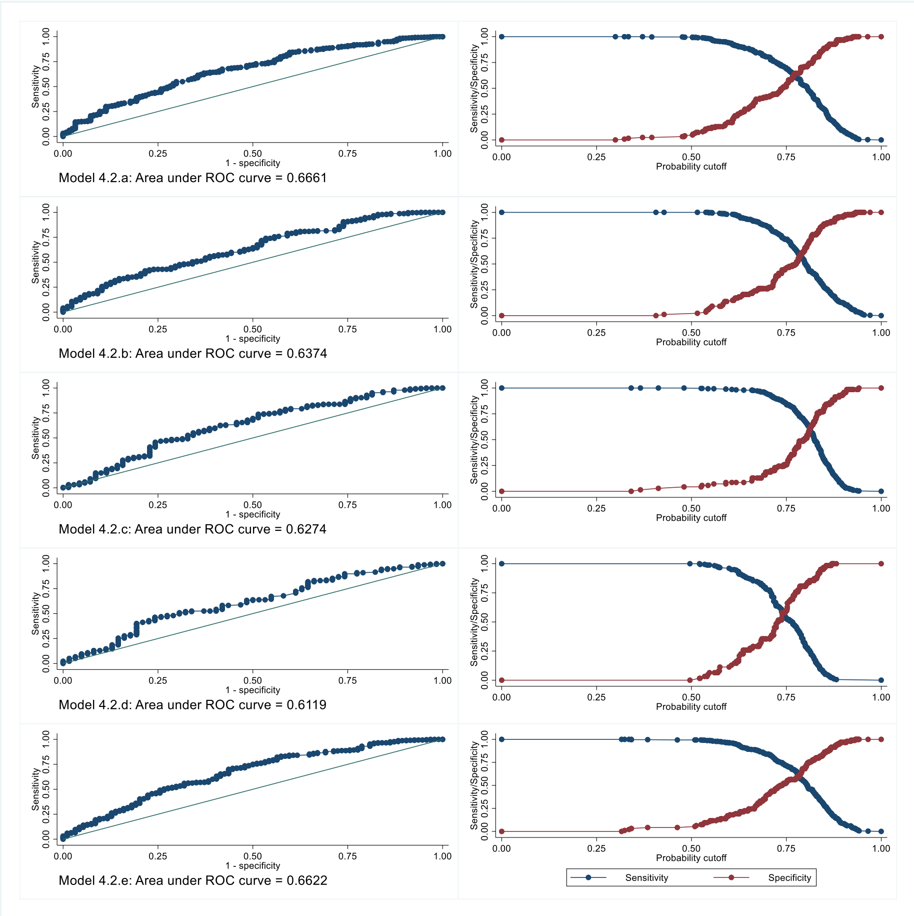


Figure B. 2 ROC analyses of Model 4.2.a, Model 4.2.b, Model 4.2.c, Model 4.2.d and Model 4.2.e.
Source: Author's preparation.
Note: This figure depicts the post estimation ROC analyses of the logit models, Model 4.2.a, Model 4.2.b, Model 4.2.c, Model 4.2.d and Model 4.2.e. Regarding the ROC comparisons, the first model, Model 4.2.e has the highest credibility in estimating the probability of choosing a pro-environmental bundle for farmers who prefer solar to fossil energy to reduce environmental damages.

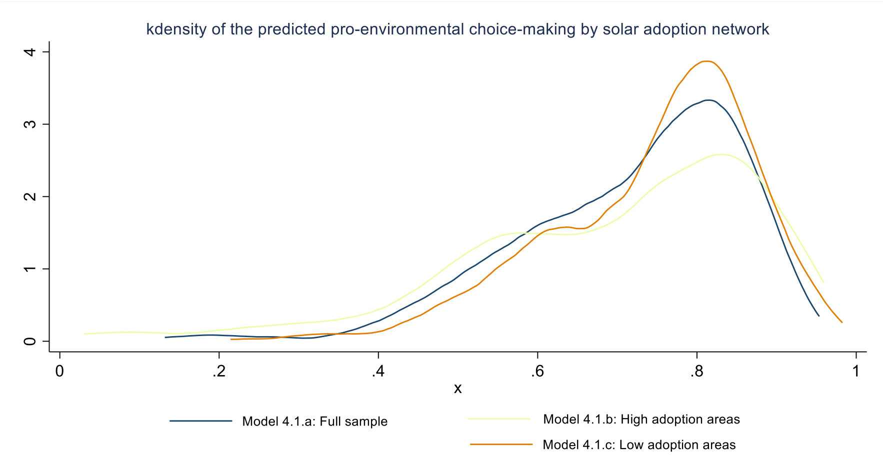


Figure B. 3 kdensity of the predicted pro-environmental behaviour for full sample, and high and low adoption areas.
Source: Author’s preparation.
Note: This figure depicts kdensity distributions of the predicted pro-environmental bundle choice in models, 4.1a, 4.1.b and 4.1.c. The predicted probability of pro-environmental bundle choice shows no variation in models with and without the effect of solar adoption network intensity. However, probabilities are to some extent volatile between high and low adoption areas.

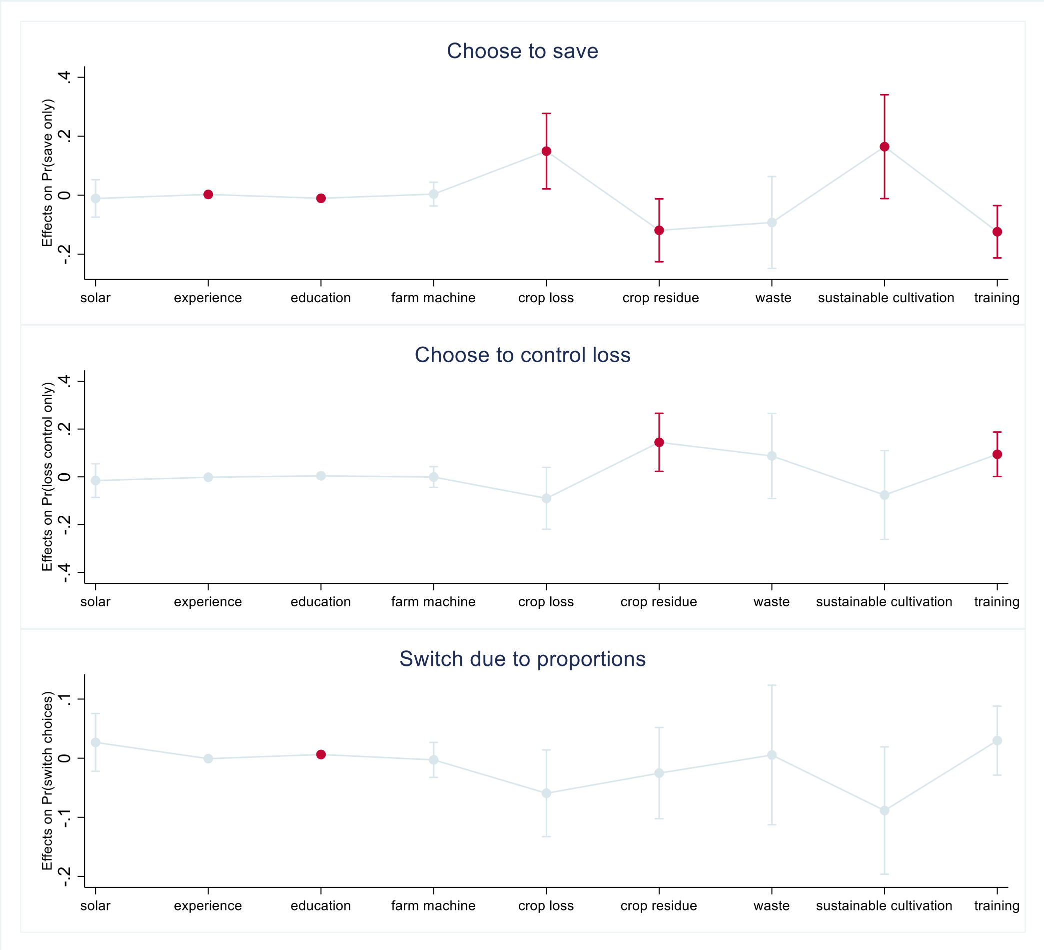


Figure B. 4 Coefficient plot of the predictors influencing the framing effect categories.
Source: Author's preparation.
Note: This figure depicts the predicted margins of the explanatory variables for the three framing effect categories (constructed). The margins predicted show pairwise variations in the effect of an independent variable on each category. This figure is produced from the estimated results of Multinomial logit model, Model 4.5. Cranberry colour represents the significant effects of the variables.

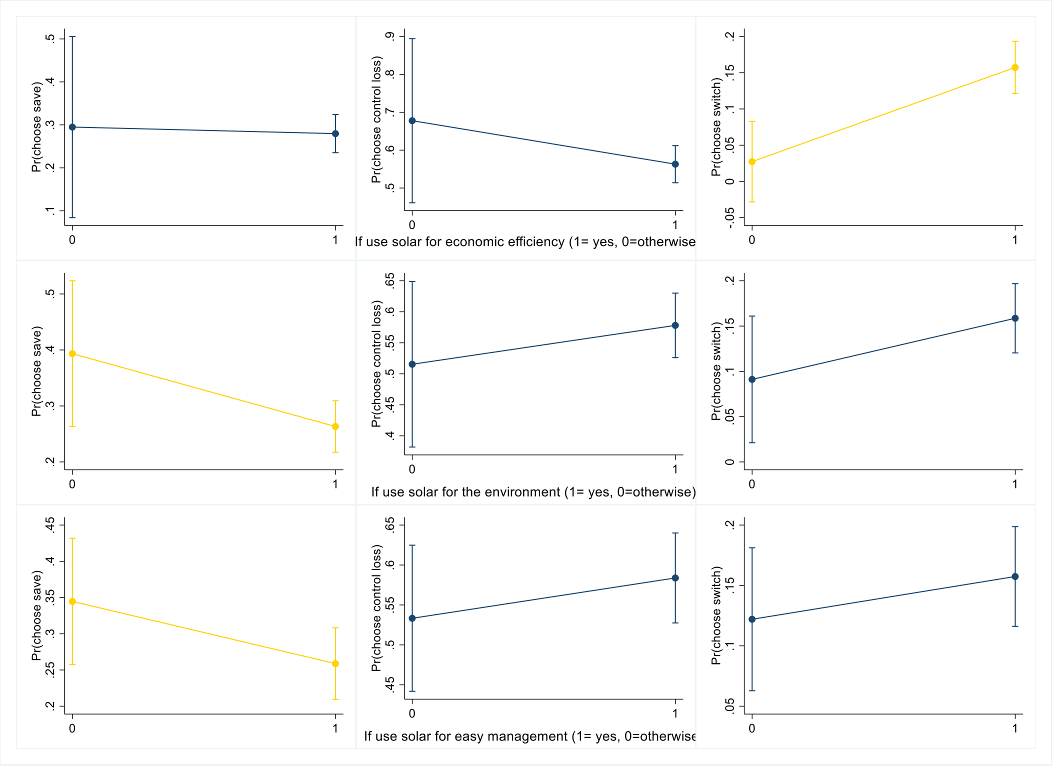


Figure B. 5 Margins of the solar use rationale influencing the three framing effect categories.
Source: Author's preparation.
Note: This figure depicts the margins of the reasons behind using solar irrigation, i.e., for economic efficiency, for environmental sustainability and for an easy management to predict the three framing effect categories. This figure is produced from the estimated results of Model 4.6, Model 4.7 and Model 4.8 (presented in Table 4.7). Yellow lines represent the significant differences in the margins between farmers' groups who perceive the respective reason and those who do not.

Table B. 1 Margins at solar categories for the three constructed outcomes of framing effects

Outcomes	Margins and significance test		
	Solar	Non-solar	Difference
Choose to save	0.2858 (0.0225)	0.3042 (0.0228)	-0.0183 (0.0325)
Choose to control	0.5675 (0.0250)	0.5778 (0.0249)	-0.0102 (0.0358)
Choose to switch	0.1467 (0.0178)	0.1181 (0.0164)	0.0286 (0.0246)

Source: Author's calculation.
Note: This table presents the multinomial logit regression results of margins of solar and non-solar users for the predicted outcomes (constructed) of framing effects. These results are produced from estimating Model 4.5. The standard errors are in parentheses.

Table B. 2 Irrigation frequency and time with the interactions of solar use and choices.

Variables	Model 4.9 Irrigation frequency: solar pro-environmental	Model 4.10 Irrigation time: solar pro-environmental	Model 4.11 Irrigation frequency: solar control loss by 80%	Model 4.12 Irrigation time: solar control loss by 80%	Model 4.13 Irrigation frequency: solar control loss by 50%	Model 4.14 Irrigation time: solar control loss by 50%
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Interaction dummy	-4.75** (2.2253)	-0.8681*** (0.2253)	-3.89* (2.2545)	-0.6783*** (0.2289)	-3.4351 (2.2807)	-0.6105*** (0.2317)
Farming experience	-0.1038 (0.0768)	0.0034 (0.0078)	-0.0996 (0.0769)	0.0042 (0.0078)	-0.1013 (0.0769)	0.0039 (0.0078)
Farmer's education	-0.6601*** (0.1965)	0.0783*** (0.0199)	-0.6470*** 0.1980)	0.0803*** (0.0201)	-0.6704*** (0.1968)	0.0763*** (0.0200)
Ownership of farm machines	4.01*** (1.1832)	0.5355*** (0.1198)	3.9308*** (1.1880)	0.5223*** (0.1206)	4.00*** 1.1862)	0.5340*** (0.1205
Crop loss frequency	-0.6832 (0.6707)	-0.2347*** (0.0679)	-0.6379 (0.6706)	-0.2260*** (0.0681)	-0.5951 (0.6704)	-0.2186*** (0.0681)
If perceive that own irrigation energy is sustainable	0.5618 (2.2615)	-1.2867*** (0.2290)	-0.0403 (2.2142)	-1.40*** (0.2248)	-0.2913 (2.1984)	-1.44*** (0.2234)
If prefer solar over fossil energy	10.50*** (2.2890)	-0.9896*** (0.2318)	10.28*** (2.2886)	-1.03*** (0.2324)	10.06*** (2.2757)	-1.07*** (0.2312)
If managing crop residue sustainably	-1.38 (3.4338)	-1.2947*** (0.3477)	-1.4409 (3.4379)	-1.30*** (0.3491)	-1.21 (3.4550)	-1.26*** (0.3511)
If managing waste sustainably	-3.5610 (4.9508)	-0.0584 (0.5013)	-3.4635 (4.9552)	-0.0395 (0.5032)	-3.47 (4.9578)	-0.0423 (0.5038)
If using any sustainable agriculture (SA)	-14.64*** (4.9839)	1.0640** (0.5047)	-15.17*** (4.9714)	0.9596* (0.5048)	-15.42*** (4.9660)	0.9180* (0.5046)
F-statistic	5.78***	18.05***	5.61***	17.32***	5.54***	17.10***

Source: Author's calculation.

Note: This table presents the OLS regression results of irrigation frequency and time controlling for the effect of solar users making pro-environmental behaviour, choosing resource control losses by 80% and 50% respectively. The standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. OLS regression process is explained in detail in Chapter 5.

Chapter 5

Cooperation in a renewable irrigation entity

5.1 Introduction

The agricultural irrigation system is a complex type of *common-pool resource (CPR)*. Irrigation devices and their operational systems are individual or collective properties depending on energy sources. Individuals in a common entity do not wish to choose an outcome that may yield lower returns for themselves separately and consequently, they realize that higher returns could be possible if they acted collectively (Ostrom and Walker, 2003). However, collective choice of input use for economic efficiency and that guided by the perception of its socio-environmental sustainability are susceptible to both individual and peer commitments. As Sen (1977) argued, commitment in an entity links choices and welfare, driven by morality and motivation. Thus, when an individual agency risks common resources and the institution becomes less efficient, collective or group governance can rectify the situation (Ostrom et al., 1999). Therefore, decision-making in common-pool management requires sincerity and motivation of each member. It is also possible that one or some individuals may be persuasive over an entity and help them adopt a decision (Sen, 1995). Each actor's choice and contribution do not remain structurally and equally either rational or ethical. As Momeni (2020) devised, there is heterogeneity in CPR users' social behaviour in terms of contribution-action in *mandatory* and *voluntary* scenarios, the latter being less effective in collective effort implementation. According to Ostrom (2009), there are some general user dispositions in common properties, namely, i) salience, ii) mutual understanding, iii) low discount rate, iv) trust and reciprocity, v) autonomy, and vi) prior local organizational experience and vii) local leadership (see Heenehan et al., 2015). Importantly, actions and outcomes even in an entity rely upon users' heterogeneity in demographics, accessibility to resources, and contributions (Ostrom, 2011a). These individual attributes are subjective and of varying nature in time and space. Attributes of social ties and networking presume peer performance and act accordingly. That is why, decision-making even in a committed or structural entity is prone to variation. Theoretical underpinning is that both information asymmetry and lack of peer communication are common problems for CPR users, leading to resource degradation and exhaustion. In CPR management, there are *appropriation* or use and *provision* or endowment problems (Ostrom et al., 1994), including the complicated process of achieving outcomes (Fehr and Leibbrandt, 2011; Momeni, 2020). This study argues that each entity is spatially and structurally different and it may face dilemmas and contradictions of its own. In this regard, there is not sufficient evidence on the nature and structure of commitments and reciprocity between users that can improve cooperation.

In irrigation, there are dilemmas of efficient management of water use and optimization of irrigation cost. There is high equipment installation cost and operating cost varies across energy sources. Past evidence also shows that individuals within an irrigation system are differentiated by the longitudinal access of their landscape to water-source (Anderies et al., 2013), pump ownership (Mottaleb et al., 2019; Nagrah et al., 2016), and land use (Su et al., 2020). Thus, an irrigation common cannot explain property rights exclusively and straightforwardly. Different pumps can use the same water sources. There are various types of pump ownership involving public and private stakeholders, e.g., individual farmer, joint, community, government, and so on. Differences in the formulation of property rights, may produce tension among users and affect collective sentiment (Khadjavi et al., 2021). Besides, there are demonstration effects and peer influence of formal and informal structures. Individual motivation may face complexities when multiple resources, stakeholders, and parties are involved in the decision-making process and management. Bazzi et al. (2021) argued that there are conflicting interests in individual and collective actions based on anti-feelings about political authority. There is evidence of positive (Buisson and Balasubramanya, 2019; Cao et al., 2020) and negative (Takeda et al., 2015) contributions of institutional governance over farming entities. According to Ostrom (2011b), in irrigation commons, institutional governance failure is due to a lack of information about actual problems faced by irrigators. In the case of irrigation, each farmer is accountable for resources, outcomes, and purposes. Irrigation cost and crop yields are each irrigator's resources and outcomes, while irrigation's economic and environmental efficiency can be a common purpose. Therefore, communication and commitment may depend on each irrigator's decisions and the extent of cooperation that an entity allows. For example, in Drouvelis and Marx (2021), if peers know each other's contributions, total charity donation increases collectively. Individual motivations and decisions mutually could induce a better collective effort. Another view could be that even if there are no communication and management failures, a structurally settled entity bounds individual action, e.g., renewable irrigation systems. In such cases, as Bazzi et al. (2021) argued if the choice of provisions influences externalities, individual rationalization may impact social responsibility and cooperation. In climate-smart irrigation, i.e., renewable irrigation the efficient use of resources (e.g., economic efficiency and easy management) may trigger both responsibility and voluntary cooperation. Therefore, this study explores if individual choice of energy technology determines the nature and type of cooperation in an irrigation setting.

In this spirit, this study aims to evaluate irrigation systems conditional upon energy use. It uses the case of Bangladesh because in this country the irrigation network has a multi-type formation of irrigation devices' ownership, watering management and payment contracts. Payment and water supply arrangements for irrigation groups vary with contract types. There are two types of contracts and accordingly payment methods. A crop contract is based on harvest and a water contract uses water use and irrigation frequency for payments (Michler and Wu, 2020). A crop contract by definition requires a higher level of cooperation and trust among users while a water contract is more flexible in terms of group code. In a water contract, external factors, i.e., water availability and climatic conditions are important. Thus, any deterioration in trusts and ties between water buyers and sellers may cause an entity failure. On the other hand, dilemmas may result from harvest commitment failure in a crop contract. Michler and Wu (2020) demonstrated that the choice of contract depends on resource location and contract experience between water buyers and sellers. Variations in ownership of water-collecting equipment and management (Hasan et al., 2020; Mottaleb et al., 2019) indicate the complexity of the association of formal and informal institutions with contracts and payment modes. In irrigation, the operation uses surface and groundwater points, and water-level depletion in the latter causes severe climate change impacts on cultivation (Alauddin and Sarker, 2014). Equally importantly, issues take multiple dimensions when using groundwater and lands located at a distance. It is possible that while using surface water, traditional and manual methods can be alternative options for lands located near the water sources. Nevertheless, deep tube wells (DTWs), shallow tube wells (STWs), and low lift pumps (LLPs) are major modes for irrigation, with second and third modes being increasingly used. According to the BBS (2020), the use of all other modes including power pumps and manual devices dropped, while the use of STWs increased by 2.19% in 2018-19. Two major sources of energy are electricity provided by diesel (78.45%) and solar and electricity (both constitute 21.55%, where the electricity network is not sufficiently wide (BADC, 2020). Therefore, considering economic and environmental viability, solar is an efficient technology using less time per irrigation and hence less costly. During dry season cultivation, when irrigation uses mostly groundwater and high horsepower pumps are required, costs may vary largely with pump ownership, contracts among farmers, and of course land features. As Ostrom (2011b) demonstrated, irrigation systems may produce unfavourable outcomes in areas with severe water availability issues. In Bangladesh, a switch to solar irrigation is happening primarily for economic and environmental reasons (SREDA, 2019). Nevertheless, in external conditions of uncertainty, technology use may become a cost-reduction strategy. Additionally, energy choice for pumps may impact cost structures and farmer-farmer relationships using the same energy and water sources. Therefore, using a field survey of farmers, this study tests and compares both cooperation behaviour and economic efficiency of solar and non-solar irrigation settings. The methodology employs- i) a logit regression model to predict contract type, ii) quantile regression processes to evaluate irrigation groups and irrigation length, and iii) mean regression processes to assess the economic and management efficiency in irrigation.

This chapter continues as follows. Section 5.2 presents a review of collective action literature and discusses the conceptual framework of this study. Section 5.3 provides a detailed description of outcome variables and empirical strategies. Results and discussions are presented in Section 5.4. Section 5.5 concludes this chapter by providing a summary of the results and policy implications.

5.2 Review of collective action literature and conceptual framework

To identify and construct the cooperation outcomes in a conditional entity, I extensively review the experimental approach to collective action in the following sections. These sections also present a critical evaluation of the past experimental designs to estimate collective action and indicators. The diversity in collective outcomes can be explained either by evaluating individual-level behavioural analysis of trust and reciprocity or by analysing aggregate-level framework that makes provisions (Ostrom, 2011b). Previous empirical investigations of collective action and behaviour used both experimental and non-experimental approaches. Experimental approach in collective action literature largely focused on public goods or resource conservation behaviour. These studies provide evidence on the strength of cooperative behaviour to address free-riding problems and to evaluate reciprocated goals. Some key insights produced in past evidence are as follows- i) individual behaviour is often pro-social (Babcock et al., 2020), ii) individually and collectively, each member is pro-environmental (Alcon et al., 2020; Bluffstone et al., 2020), iii) cooperative attitude and existing social capital increase sustainable choice of resources and utilities (Barr et al., 2020; Bluffstone et al., 2020; Gelo, 2020; Khadjavi et al., 2021), iv) reciprocity produces spill-over effects and encourages shared consumption (Khadjavi et al., 2021), and v) collective effort reduces transaction cost and removes any informational asymmetry (Gelo, 2020). Babcock et al. (2020) in their intervention-based experiment observed that gym-visit increases with friendship network. Three dimensions of peer mechanism is explained in their study, namely coordination, imitation and information exchange, where coordination is measured by timing decided to exercise together perceived as time could be enjoyed with a friend and transport cost could be shared. The results in Alcon et al. (2020) suggest that achieving environmental benefits is a social choice which requires active participation of increasing number of individuals. Relevantly, peer identification is a determining factor in social endowments (Drouvelis and Marx, 2021). The reason might be that individual utility and actions are related to *sympathy* and *commitment*, the latter being less self-oriented (Sen, 1977). However, the quality and content of information received from peers and about peers affect individual action (Herskovic and Ramos, 2020). This suggests that if peers are acquainted with each other, they become more confident about others' motivation. Even though, perception of environmental degradation at global level may not motivate individual action as observed in Grolleau et al. (2020). It implies that any sustainable action becomes socially acceptable if actions and outcomes are spatially relevant. Khadjavi et al. (2021) separately estimated trust and reciprocity attitude of smallholders towards solar-use as a common resource. They found significant trust in village communities and its correlation with spill-over effects of successful experiences of other communities. Likewise, trust factor dominates in Fisman et al. (2020), as common schooling background positively influenced the likelihood of political candidate selection. It suggests that social capital components are tightly bound in a spatial space, and yet that can be revised subject to experience, knowledge and education. Experience in any previous collective effort is an important factor encouraging new decisions (Bluffstone et al., 2020; Gelo, 2020). For a forest product marketing cooperative member, their children's education and off-farm employment received importance in Gelo (2020). Bluffstone et al. (2020) found positive impact of any group involvement on experimental public good conservation behaviour. In Kong et al. (2021), farmers' training-led experience could promote collective practice of conservation agriculture. From the previous evidence, it appears that perception of mutual benefits, cognitive psychology about peer behaviour and individual practices, explain collective behaviour and action. Mutual understanding becomes a key behaviour if choices forwarded by different social groups have various purposes of responsibility and ethical concerns (Sen, 1977). However, these findings do not sufficiently explain the robustness of collective behaviour if both economic and environmental efficiencies are involved.

Estimating payment for ecosystem services (PES) is one approach to evaluate how communities perceive of and prioritize between economic and environmental sustainability of commons (Barr et al., 2020; Dardanoni and Guerriero, 2021; Kolinjivadi et al., 2019). This strand is largely based on open access resources and choices for evaluating motivation mostly involve financial retribution. PES experiments mostly assume individual rationality as consistent with social obligation (Kolinjivadi et al., 2019). Barr et al. (2020) demonstrated that contribution to public good conservation increases if there is higher return collectively. An important finding in their study is that individual return does not have any impact on conservation behaviour, providing an indication of individual non-rationality. Dardanoni and Guerriero (2021) estimated environmental protection intention across different adolescent and young groups. The authors found that even if there is overall positive attitude towards protection, active participation depends on monetary allowance and a perception of disutility. Similarly, in Li et al. (2020), middle-aged and young farmers show a larger tendency of using electronic technology in farm produce sales. It seems that users' accessibility is an influential factor to steer community's environmental motivation.

There is another common experimental approach to understanding cooperation, i.e., testing 'conditional cooperation'. For example, in Kunwar et al.

(2020), households wish to pay for water-system management more if the resource remains common-pool. Such preference for decentralization of public good provisions is a possible solution to the appropriation dilemmas and this improves cooperation (Bouma et al., 2014). However, individual behaviour in such contexts may remain presumptuous about oneself and peer reaction (Frey and Meier, 2004). To test conditional cooperation, most studies used trust games in public good experiments in a single round (e.g., Khadjavi et al.,2021) and in multiple-rounds (e.g., Cason et al., 2017). These games mostly use payment choices between individual and group accounts and a collective purpose to elucidate individual rationality and social norms. Behaviour often differs with and without communication during experiments, explaining the strength of communication and peer relations (Cason et al., 2017). There is also a difference in behaviour depending on group size and accordingly the level of trust that group holds (Campos-Mercade, 2020). Campos-Mercade (2020) demonstrated that an individual belonging to a larger group is likely to help a *victim* due to a *volunteering dilemma* and bigger groups receive help early. However, most previous peer trust games do not consider pre-existing social capital and actual resource-user. Conditional cooperation is a mere chance of acquaintance, which may or may not reveal social norms that participants usually follow. In contrast, D'Exelle et al. (2018) examined the channels of explaining cooperation through communication, controlling for social ties, public programme involvement and gender relations. Nevertheless, the nexus of communication-cooperation was the effect of programme participation. Brocas et al. (2021) used a non-monetary activity-based approach in a dictator game between producers and consumers. The authors demonstrated that psycho-social reasoning (e.g., a feeling of shame) of an individual can be estimated separately even if there is no monetary gain. Prediger et al. (2014) observed that the likelihood of anti-social behaviour is higher in areas facing a larger resource scarcity. The authors also found that individual prediction about peer behaviour increases such anti-social behaviour. Resource competition can deteriorate trust level. Similarly, trust level reduces festival contribution in Bouma et al. (2014). In Vorlaufer and Vollan (2020), when competition and inequality between local and migrant communities increased, wealthy migrants contributed more to public services and cooperative motive remains intact. These studies suggest that an individual may not cooperate voluntarily for social welfare. In addition, an individual may not cooperate to preserve common resources. Instead, features of an entity could explain its members' cooperation behaviour.

Regarding experimental approach in cooperation and collective behaviour studies, there is a debate around its external validity of lab and field experiments. The reason might be that irrespective of designs and contexts, such experiments produce mixed outcomes (Bluffstone et al., 2020). Even designs and participants themselves may cause behavioural inconsistency. Bosch-Rosa and Meissner (2020) showed that cooperation improves if participants understand game features, because they can effectively perceive others' responses and act accordingly. Brocas et al. (2021) observed significant differences in consumer response when multiple rounds are played with and without intervention cases. According to Levitt and List (2007), external validity depends on a) moral considerations, b) assessment of own and others' actions, c) context of experiment, d) respondent type and e) game risks (also see Bouma et al., 2014). It is also possible that behaviour becomes inconsistent between hypothetical and actual settings. In most payoff choice experiments, games are played multiple rounds to estimate collective behaviour. One particular concern might be that components of collective behaviour are not directly measurable (Khadjavi et al., 2021).

In payoff designs, comparative payment allocation between individual and group accounts measures social dilemmas. For example, Bouma et al. (2014) utilized a community religious festival where financing is an individual decision and festival participation is non-excludable, an example of compulsory cooperation. Collective behaviour in this case might be overestimated. The reason is that during cultural and religious festivals, collective participation is generally appreciated irrespective of financial contribution.

Another issue in collective action literature is that open-access resources received the most attention. An early study by Fehr and Leibbrandt (2011) observed the link between fishing instruments and collective response toward fish stock exploitation. Their study found that fishermen are likely to cooperate perceiving the stock exploitation and use accordingly a required technology as a control tool. Bluffstone et al. (2020) observed that a cooperative attitude is likely among forest users, depending on their previous individual plantation practices and biogas investment. Regarding water-system settings, Anderies et al. (2013) observed that cooperation depends on the land length of the water point and water availability. The authors argued that these two factors create an interdependent relationship between water-labour provision and a likely social dilemma between users living near and far from water points. Employing a three-stage investment game, they found that cooperation does not improve when water becomes scarce. However, their findings are based on laboratory experiments on students, rather than on irrigators, i.e., actual water users. In Meinzen-Dick et al. (2018), cropping choices are given with varying water consumption, to test individual cooperation in possible water-stress scenarios. The authors estimated the probability of choosing water consumption in two different periods and found that choice exhibits considerable heterogeneity in communication, trust, and water availability. Open access resources are direct livelihoods. Thus, cooperation for resource sustainability is likely for the sake of individual economic benefits even though interdependence is not mandatory. However, unlike open-access resources, economic and environmental behaviours are not directly complementary in an irrigation system. Another key difference is that, in the latter entry and exit are more restricted due to fixed locations of farmland and water sources. Conditional cooperation is embedded in such a confined or structural system, implying every individual irrigator is bounded by a common irrigation method and compulsory interdependence. Therefore, cooperation could be more inclusively sensitive to entity dispositions and irrigation methods.

I draw three general conclusions based on this overview. Firstly, demographic characteristics and social capital exhibit heterogeneous impacts on the internal condition of an entity. Secondly, external conditions of an entity, namely the size of an entity and the type of a common arrangement (structural or conditional) may produce mixed motivations for the cooperation of each party in that entity. Thirdly, there is an intervention effect on cooperation behaviour. On such bases, the questions remain- i) which features of a group impact cooperative behaviour? ii) is a structural entity an obstacle or advantage to achieving common sustainability goals? and iii) what are the structural and operational conditions of cooperation that improve an entity's efficiency? Referring to Khadjavi et al. (2021), trust and reciprocity are crucially fundamental in an irrigation common. As Sen (1977) explained, behaviour based on commitment is comprehensive, including outcome evaluation and a sense of responsibility, which widens individual instincts and reasoning. This study employs a natural experimental approach to compare two core cooperation dispositions of solar and non-solar irrigators, i.e., commitment and reciprocity. Firstly, to assess the features of an entity that may impact commitment, I estimate the impact of energy technology on- i) irrigation contract type (i.e., if choose a long-term contract) and ii) irrigation group (i.e., if the size of an entity is big). Irrigation contract type and irrigation group are the proxy measures of cooperation commitment. The variable, *if using solar irrigation* sheds light on farmers' environmental commitment as well. Then I evaluate reciprocity by- i) testing the differences in contract choice for various reasons behind a contract choice (i.e., why an entity uses sustainable technology), ii) predicting irrigation length (i.e., if structural land conditions matter in collective choice of sustainable technology) and iii) evaluating irrigation efficiency (i.e., in what cooperation conditions an entity's resource efficiency improves).

5.3 Materials and methods

This study creates a natural experiment (NE) by a random assignment of solar users after the installation of solar plants in an area. Natural experiments have been used to observe the causal effects of natural phenomena and public policies (e.g., Grove and Wasserman, 2006; Irani and Oesch, 2013, Hanna and Oliva, 2015; Hartzmark and Sussman, 2019; Perez-Truglia, 2020; Rahman et al, 2020; Ji et al, 2023). Using solar is a natural event in the sense that this study did not control the assignment of farmers to solar irrigation. In addition, the selection of areas for solar irrigation is orthogonal to cooperative outcomes, and pre-assignment does not address socio-demographic variables and farm characteristics. Local geographical and agricultural scenarios are the main criteria for solar plant installations. Farmers do not know the exact location before they are installed. They do not receive information on capacity and efficiency. However, solar energy could be a self-selection case when a group of farmers farming together previously wish to use it. NE approach reduces the effect of confounding variables and responds to the problem of self-selection of treatment groups (Roe and

Just, 2009). Thus, even if solar use is not perfectly random due to fixed farmland locations and a group's strategic interest in renewable energy, its *near randomness* (Rosenzweig and Wolpin, 2000) makes it suitable to examine its effect in a natural experimental design. This study uses four types of regression models to estimate nine outcome variables (one binary categorical variable and eight scale variables). The following sections define the outcome variables and discuss their measurements and the regression processes.

5.3.1 Outcome variables

Irrigation contract

The outcome variable, *irrigation contract* is a binary categorical variable, coded 1 if the farmer uses a crop contract, and 0, otherwise a water contract. These two contracts are distinct categories in terms of payment arrangements and irrigation management. In a crop contract, a pump operator manages irrigation, and payment arrangement uses a post-paid flat irrigation fee crop-wise for the entire season. Fee calculation is mainly based on crop-yield or land productivity received and operationally, it is a long-term contract. On the other hand, in a water contract, each farmer calls for irrigation and a fee is based on water use each time. That means the fee is pre-paid, and the charge is per hour of water flow. Thus, the total fee depends on land size, implying the higher the amount of land, the longer the irrigation time. Payment arrangements also suggest that coordination and cooperation behaviour among farmers irrigating together differ by contract type. Since crop contract is a more comprehensive setting, on irrigation days a larger level of group reliability and peer trust is required for mutual yield gains. In a water contract, these factors are secondary since irrigation is an individual requirement. However, cooperation in such a contract also becomes important if a larger group is using the same pump. Thus, irrigation group size is likely to determine the level of cooperation. I test the following hypothesis:

H5.1: Solar users are more likely to choose a crop contract than non-solar users.

Irrigation group

I operationalize the *irrigation group* as the number of farmers irrigating together. I use two outcome variables to measure the irrigation group. The first is the irrigation pump user group, i.e., the number of farmers using the same pump and the second is the irrigation water user group, i.e., the number of farmers using the same water source. Locations of pumps and water sources may be different for farmers, particularly for non-solar users and irrigation groups that use surface water. A larger group suggests a higher degree of cooperation. In the study area, both solar and electricity users irrigate in large groups (Table 5.3). Irrigation contract type could explain cooperation differences to some extent. Even if the users' group size is large, it may not capture cooperation entirely. A group including big farmers may differ from a group including small and marginal farmers. The total land amount cultivated against a pump or water source is not homogenous across irrigation groups. Thus, the water supply may or may not affect the most distant lands. This implies that irrigation length remains crucial for cooperation behaviour. I test the following hypothesis:

H5.2: An irrigation group is bigger in solar-use than in non-solar use.

Irrigation length

The outcome variable *irrigation length* uses two measures, i.e., the distance of the cultivated land from a pump and the distance of the cultivated land from a water source. Distance is measured in meters and starts at the first boundary of the land.

Distances differ by energy use and water source. However, distances of land from a pump and from a water source do not differ for farmers using groundwater sources. Generally, two or three energy sources of irrigation are available in each location or village. Sometimes two technologies operate in close proximity. Particularly for solar irrigation choice, primary structural conditions include- i) the size and capacity of a pump and ii) the location of that pump. The first condition determines the size of users or the size of total land irrigated with a single pump. For the second condition, farmers' cooperation motive is crucial, because peer farmers decide on using a pump and sometimes on the location of a pump (particularly in case of solar pumps). Thus, even if the location of land is fixed, farmers' choice of drawing water from a pump reflect their cooperation and peer relations. It is observed from the field survey that farmers switched an irrigation contract (44% in the full sample and 70.75% of the solar users) because of water supply issues (62%) and pump location (20%) which are directly and inclusively related to irrigation technology. While using irrigation technology, its management includes timing, queue, and the amount of water supply. Such management issues may lead to water conflicts, e.g., between close and distant landowners and that would impact the level of cooperation. Thus, measures of distances are important indicators to examine the cooperation robustness in solar irrigation, e.g., if distances from a pump and a water source are longer in solar irrigation than in non-solar irrigation. I test the following hypothesis:

H5.3: Solar users irrigate at a longer distance than non-solar users.

Irrigation efficiency

Four outcome variables measuring *irrigation profiles* reflect if irrigation is economically efficient. To elaborate, irrigation that takes fewer days, and less time, incurs less cost, and ensures higher land productivity, is economically efficient. Mean annual irrigation frequency is the average number of days for irrigating lands for all crops in a year, i.e., a crop calendar. Mean annual irrigation time is the amount of time per irrigation. Irrigation time varies across seasons and water availability. Therefore, irrigation time for summer, winter, and monsoon seasons is separately collected and then average hours per irrigation for a crop calendar is calculated. For the mean annual irrigation cost measured in Bangladeshi currency, the mean irrigation charge is inclusive of all crops cultivated in a year. Finally, mean annual land productivity is the ratio of the average land amount cultivated (in decimals) and average crop yields (in kilos) in a year. Bangladeshi farmers farm the same amount of land in three seasons annually. Thus, their cropping intensity is high and they follow three cropping patterns- mono, multi, and inter patterns. In the study area, most of the farmers (76% approximately) grow only rice, i.e., they follow rice mono-cropping, and 21.25% and 23.50% follow multi- and inter-type patterns respectively. However, I observe similar density distributions for these indicators for all crops annually cultivated. Farmers in the study area cultivate rice in three seasons, and wheat, maize, jute, lentil, and vegetables irrespective of cropping patterns. Choice of crops are similar for solar and non-solar using farmers. Therefore, I use mean annual accounts of all economic efficiency indicators for a farmer instead of taking them per crop. I test the following hypothesis:

H5.4: Economic efficiency is higher in solar irrigation than in non-solar irrigation.

5.3.2 Empirical strategy

5.3.2.1 Logit regression

I use the following linear predicted model of outcome variable y_i for the crop contract choice:

$$y_i = \alpha_0 + \alpha_1 T_i + \acute{\beta} X_i \qquad \text{Equation 5. 1}$$

Here, I estimate the probability of using a crop contract (coded as 1). The probability of using a crop contract takes place in terms of log odds as a linear combination of the selected explanatory variables. The probability of $y_i = 1|treatment_i, X_i$ ranges between 0 and 1 and the logit function is, $p_i = \frac{1}{1+ e^{-(\alpha_0 + \alpha_1 T_i + \acute{\beta} X_i)}}$. The expression, $1 - p_i = \frac{1}{1+ e^{(\alpha_0 + \alpha_1 T_i + \acute{\beta} X_i)}}$ is the probability of $y_i = 0|treatment_i, X_i$. The logit model is estimated as follows:

$$\ln\left(\frac{p_i}{1 - p_i}\right) = \alpha_0 + \alpha_1 T_i + \acute{\beta} X_i + \epsilon_i \qquad \text{Equation 5. 2}$$

From equation (5.2), $\alpha_1 = \left(\frac{\partial p_i}{\partial T_i}\right)$ estimates the probability of using a crop contract if a farmer uses solar irrigation and ϵ_i is the random component. An odds ratio higher than 1 implies that the odds of using a crop contract are higher for solar users than for non-solar users. The marginal effect explains the effect (i.e., magnitude) of being a solar user on the probability of using a crop contract. Finally, the margins, i.e., average predicted probabilities of crop contract use at specified values of solar irrigation use, i.e., $solar = 1$ and $non - solar = 0$, are compared. This process also uses three interaction terms. Thus, margins show heterogeneity in crop contract choice between i) solar users receiving agriculture-related information and non-receivers, ii) solar users receiving agricultural subsidies and non-receivers, and iii) solar users having a different contract previously and not having a different contract.

I estimate six different logit models- i) without controlling for solar users' institutional accessibility and farm characteristics, ii) controlling for solar network intensity, i.e., high and low adoption areas separately, iii) controlling for farm characteristics, such as soil type and land elevations (low, medium and high), iv) for farmers who follow an irrigation contract for economic efficiency, v) for farmers who follow a contract because of peer pressure and vi) for farmers who use a contract for water management.

5.3.2.2 ANOVA

This study uses a one-way analysis of variance (ANOVA) to show the variations in scale outcome variables by energy use. ANOVA is a non-parametric multi-comparison approach for groups with more than two categories. For an outcome variable, y_i with i number of categories and j number of observations, the one-way ANOVA model is expressed as:

$$y_{ij} = \mu + \alpha_i + \varepsilon_{ij} \qquad \text{Equation 5. 3}$$

Regarding calculations, this process produces the sum of squares (SS), a mean square (MS), the F-statistic, and its significance level. ANOVA test also decomposes the sum of squares into between groups sum of squares, within groups sum of squares, and a total sum of squares. This study originally found three categories of farmers on the basis of energy use, i.e., solar users, diesel users, and electricity users. In ANOVA, between groups sum of squares is defined by the sum of the squared distance of each group or mathematically, $S_1 = \sum_i w_i \, (\bar{y}_i - \bar{y})^2$. A value of S_1 other than zero indicates that the mean of each group differs from the total mean. The higher the value, the larger the difference. Within the group sum of squares is the error or residual sum of squares. A significance test confirms that at least one of the three categories differs in the respective outcome variable. After receiving the indication of group differences in the ANOVA process, the sample t-test gives further validation of the formations of solar and non-solar categories. ANOVA process also performs a variance homogeneity or heterogeneity test, i.e., Barlett's equal variance test. The null hypothesis is that variance is homogeneous and a significant χ^2 will indicate evidence against this hypothesis. This tool will also decide on the appropriate regression process to predict an outcome variable conditional on energy use.

5.3.2.3 Mean regression

I estimate a mean regression model to observe the effect of solar irrigation use on scalar outcome variables of irrigation management and economic efficiency. The outcome variables include i) irrigation group, ii) irrigation length, iii) mean annual irrigation frequency, iv) mean annual irrigation time, v) mean annual irrigation cost, and vi) land productivity. This process uses the following equation for each scale outcome variable:

$$y_i = \alpha_0 + \alpha_1 T_i + \hat{\beta}\acute{X} + \varepsilon_i \qquad \text{Equation 5. 4}$$

Here, α_1 estimates the effect of a farmer using solar irrigation on the respective outcome variable. The sixth model here uses a log-level mean regression and the rest uses level regression models. The variance inflation factor[13] checks multicollinearity for each OLS regression. This process calculates the fitted values (i.e., mean response values) of scale outcomes and visualizes the margins of solar and non-solar users for the linear predictions. The mean processes are conducted for the full sample, and high and low adoptions areas separately. The sub-sample analyses are conducted for crop contract, water contract, irrigation equipment ownership, government-owned pumps, surface water use and groundwater use.

[13] Appendix D includes the details of the test.

5.3.2.4 Quantile regression

The quantile regression models the relationship between conditional quantiles of the dependent variables (irrigation groups and irrigation lengths) and the variable of interest (solar irrigation use). I observe that irrigation group size (i.e., the number of farmers using a pump and/or a water source) and irrigation length (i.e., the distances of cultivated land from a pump and a water source) do not remain the same in energy use across farmers (Table 5.3). There are solar and non-solar pumps of various capacities serving different numbers of farmers and in various radiuses. Solar pumps with similar capacities do not provide water to an equal number of farmers in all irrigation settings. Moreover, non-solar farmers are not homogenous as I combine diesel and electricity sources for this group. Electricity users irrigate lands in larger groups and longer distances as solar users do. In such a situation, estimating irrigation groups and irrigation length by energy use at the mean could not give their inefficient estimates. In addition, conditional means in such processes do not explain the nature of the effect of solar irrigation use on the longer tails of the distribution of irrigation groups and lengths. Therefore, I use median (quantile) regressions, instead of mean regressions for four outcome variables, namely i) pump user group, ii) water user group, iii) from land to pump distance, and iv) from land to water distance. There are two major benefits of using a quantile regression approach. This approach does not make any assumption about data distributions, deals with the heterogeneity of variance, and uses even outliers while predicting a scaler outcome variable (Koenkar and Bassett, 1978; Cameron and Trivedi, 2005). The following section describes the empirical models and regression processes.

The quantile regression model expresses that a quantile of the conditional distribution of a random variable is a linear function of a set of independent variables.

Thus, the inclusion of multiple quantiles in such a regression process allows for variation in the prediction of outcome variables over quantiles or different groups of observations. For example, Demir et al. (2022) showed that financial inclusion impacts on inequality reductions are higher for the upper income groups. Barry and Rousselière (2022), studied farmers' cooperation behaviour by quantile modelling and demonstrated that payment incentives do not stimulate such behaviour for cooperatives of all sizes and even positive impacts differ across cooperatives. I model the quantiles of irrigation groups and irrigation length as linear functions of the variable, *if use solar irrigation* (coded as $Yes = 1$ and $no = 0$) and a vector of independent variables that includes scaler variables (number of household members, irrigation pump capacity and mean annual cultivated land) and some binary variables (*if receive agriculture information*, *if receive agriculture credit*, *if have urban market access*, *if have clay-type land*, and *if have low elevation land*). Such a modelling process assumes an outcome variable, Y with a probability distribution function $F(.)$ conditional on $\acute{X}_i$, thus $F(y_i|\acute{X}_i) = p\,(Y \leq y_i)$ and $y_i = \alpha + \acute{X}_i\hat{\beta}$. Quantiles are defined as τ and the probabilities of τ remain between 0 and 1. For irrigation groups, I take three values of τ $(0.25, 0.50, 0.75)$ and for irrigation length variables, I take four values of $(0.25, 0.50, 0.75, 0.95)$. Now, for any value of τ, its quantile of Y is an inverse function and is expressed as:

$$Q_\tau(y_i|\acute{X}_i) = f^{-1}\left\{y_i: F(y_i|\acute{X}_i) \geq \tau\right\}$$

To estimate the τ^{th} quantile of the distribution of y conditional on $\acute{X}_i$ the equation is as follows:

$$Q_\tau(y_i) = \alpha_\tau + \beta_\tau\acute{X}_i \qquad \text{Equation 5. 5}$$

For example, the 25th quantile of the distribution of y conditional on x is given by $Q_{0.25}(y) = \alpha_{0.25} + \beta_{0.25}\acute{X}_i$. In general, the threshold is, $\alpha = \{-\ln(1-\tau)\}^{(\frac{1}{k})}$ and parameter estimate, $\beta = \lambda\{-\ln(1-\tau)\}^{(\frac{1}{k})}$. Thus, y becomes a function of $x, \tau, \lambda,$ and k. In a quantile regression process, the optimization involves the minimization of the sum of absolute deviations. One important assumption in this process is that model errors are independent and identically distributed (i.i.d.) (Cameron and Trivedi, 2005). Now, let ε_i be the residual and $\varepsilon_i = y_i - \acute{X}_i\hat{\beta}_\tau$, so the objective function for minimization is:

$$c_\tau(\varepsilon_i) = \tau - I\{\varepsilon_i < 0\})\,\varepsilon_i.$$

Here, I(.) is the indicator function and the objective is to choose $\hat{\beta}_\tau$ that minimizes $c_\tau(\varepsilon_i)$ and consequently to find the best estimates for the τ^{th} quantile of the distribution of y conditional on X.

5.3.2.5 Mean regression with instrumental variables

The instrumental variable regression is used for a robust analysis of the impacts on the economic efficiency of using solar irrigation. Solar irrigation is a given intervention and being a solar irrigation user may not be random. Accordingly, the mean regression process can produce biased estimates of irrigation frequency, irrigation time, and irrigation cost. Both solar and non-solar users can irrigate their lands in larger irrigation settings. For instance, the average group size for solar is 42 and the same for non-solar users is 24. The non-solar group includes both diesel and electricity and a maximum of 60 farmers can irrigate together using national grid electricity. For diesel users, the maximum group size is 17. Even if the group size is fairly big for diesel users, farmers do not use pumps simultaneously. Diesel users irrigate in turn by renting machines and electricity users are less considerate about energy viability. Therefore, a bigger pump use group does not necessarily indicate high coordination. That is why, regression coefficients at the mean cannot elucidate the impacts of contract arrangements on economic efficiency that may be sensitive to solar irrigation. Arrangements include the number of farmers irrigating together (e.g., pump use group) and if there is a history of a contract change that may or may not be due to an energy switch. Even if energy choice is self-selected, contract arrangement is random. This study uses 'coordination' as an instrumental variable for solar irrigation, an interaction variable of group size, and a different contract type in the past. The coordination variable is coded 1 for high coordination (if the user group size is at least 17 and higher than 17 and had a different contract type previously) and 0, otherwise or low coordination.

In this stage of regression process, I evaluate a linear instrumental variable for a scale outcome variable, Y_i conditional on a vector of exogenous predictors, $\acute{X}_{i,}$ and an endogenous predictor, T_i. Then, the models to be estimated are as follows:

$$Y_i = T_i\alpha + \acute{X}_i\beta + u_i \quad \text{Equation 5. 6}$$

$$T_i = Z_i\gamma + \acute{X}_i\delta + v_i \quad \text{Equation 5. 7}$$

For these two models, both $\acute{X}_i$ and Z_i are independent of u_i and v_i. However, the possible endogeneity of T_i suggests that $E\ (u_i v_i) \neq 0$ and consequently, $E\ (T_i u_i) \neq 0$. Thus, if prediction only involves equation (5.6), estimates will be biased. Therefore, it requires a two-stage regression process and by substituting for T_i in equation (5.6) the model for estimation becomes:

$$Y_i = Z_i\varphi + \acute{X}_i\lambda + U_i \quad \text{Equation 5. 8}$$

Equation (5.6) is the structural form, equation (5.7) requires the first-stage estimation (in a logit regression), and then equation (5.8) refers to the second-stage estimation (a mean regression).

In this two-stage process, it is assumed that the instrumental variable satisfies the conditions of relevance, independence, and exclusion restrictions. By relevance, it means that IV impact on solar irrigation use in the first stage is statistically significant. IV is random implying its independence with the error term, (i.e., v_i in equation 5.7). Lastly, the exclusion criteria suggest that IV impacts the outcome variable through endogenous variables, i.e., solar irrigation use. Thus, a larger group using solar irrigation and who had a contract switch could influence irrigation efficiency indicators substantially. Thus this process receives an unbiased estimate, $\varphi = \alpha\gamma$ that is the impact of T_i on Y_i through Z_i. Here, Z_i is the instrumental variable (IV) for T_i. The instrumental variable regression approach is a suitable choice to handle selection bias and the endogeneity problem (e.g., Sellare et al., 2020; Ma et al., 2021). However, there are issues of choice for instruments, i.e., the inclusion of weak instruments. Andrews et al. (2019) suggest that a significant F-statistic higher than a value of 10 (a rule of thumb) can validate the relevance assumption.

5.4 Results and discussions

5.4.1 Descriptive statistics and sample balancing tests

The following Table 5.1 and Table 5.2 show group differences and similarities in the explanatory and outcome variables. Solar and non-solar adopters differ in the involvement of any non-farm activity, soil type and land elevations, pump capacity, contract period and different experience of contracts, urban market access, mean annual cultivated land, and mean annual yield. Except for the contract period, mean annual cultivated land and mean annual yield, solar users have higher frequency percentages of these variables than non-solar farmers. Groups have similar household size, accesses to agricultural information and credit, possessions of medium land elevation, and patterns of groundwater use. Groups differ significantly in all outcome variables (Table 5.1 and Table 5.2). Solar users (68%) mostly follow crop contracts, while only 21.25% of non-solar users follow this type. From ANOVA analysis, it is evident that at least one type of energy users among solar, diesel, and electricity groups differs in outcome variables. Only mean annual land productivity does not vary between the three types of energy users and hence solar users' land productivity does not differ from that of non-solar users. However, there are slight result differences in ANOVA and sample t-tests.

It also appears that irrigation group size is bigger for solar users than for non-solar users. A larger number of solar users (mean is 42.66) use the same pump together than non-solar users (mean is 24.32). Accordingly, the water group size is bigger in solar use (mean is 42.66) than in non-solar use (mean is 30.11)[14]. Solar and non-solar users do not differ in land-to-pump length. The reason is that the non-solar category includes electricity users as well. However, solar users can draw water from a longer distance (2298.64 meters), while the mean distance of land from water is quite small for non-solar users (834.9 meters). All outcome variables of irrigation efficiency, i.e., frequency, time, and cost are higher for non-solar users. Solar users irrigate 4.23 days less, for 1.81 hours less, and at BDT2374.16 less cost. Relative change in mean annual land productivity is higher for solar users (1.88) than for non-solar users (1.79). Significant Bartlett's tests for all outcome variables suggest that variances are not equal for all farmers. That is why, skewness, kurtosis, and quantiles of the data distributions of these variables are calculated (Table 5.3). The distributions of all outcome variables are highly skewed with longer tails or larger outliers. However, pump-use and water-use group data distributions for non-solar users have lighter tails than normal distributions. Outcomes of irrigation group variables and irrigation length variables largely vary across sample percentiles. Solar users irrigate in a bigger group

[14] The mean values of irrigation group of using the same pump and water source is similar for solar users. However, mean values of these two outcome variables are different for non-solar users due to missing values. Not all diesel users knew the number of water source users. Section 5.4.3 explains the estimation issues of missing values of this outcome variable, i.e., irrigation group of water use.

in both lower and upper quantiles, while non-solar users' pump group becomes bigger in the upper quantile (starting at the 50^{th} percentile). Irrigation distance, irrigation frequency, time, and cost all increase largely in the upper quantiles for both groups (starting at the 75^{th} percentile). However, values differ significantly for each percentile of both groups. Small differences are observed in these variables in upper quantiles and groups differ substantially in the upper quantiles (75^{th} and 95^{th}) for the mean annual irrigation time and mean annual irrigation cost. The upper and lower quantiles of both groups do not vary largely in the relative change in land productivity distribution.

Table 5. 1 Descriptive statistics of the explanatory and cooperation outcome variables.

Sl. No.	Variables	Full Sample Mean/ frequency	Solar adopters Mean/ frequency	Non-solar adopters Mean/ frequency	*p*-value of difference
A.	**Explanatory variables**				
1.	Household size (Number of household members)	4.02	3.98	4.06	0.2608
2.	Involvement in any non-farm activity (1= yes, 0= no)	21.75% (yes)	24.50% (yes)	19.00% (yes)	0.0595
3.	If receive agriculture information (1= yes, 0= no)	65% (yes)	67% (yes)	63% (yes)	0.2361
4.	If receive agriculture credit (1= yes, 0= otherwise)	14.88% (yes)	15.25% (yes)	14.50% (yes)	0.7660
5.	Clay-type cultivated land (1= yes, 0= no)	56.13% (yes)	60.25% (yes)	52% (yes)	0.0187
6.	If have low elevation land	71.25% (yes)	74.75% (yes)	67.75% (yes)	0.0287
7.	If have medium elevation land	26.63% (yes)	27% (yes)	26.25% (yes)	0.8106
8.	If have high elevation land	36.25% (yes)	39.75% (yes)	32.75% (yes)	0.0395
9.	Irrigation pump capacity (kWp)	10.07	12.87	7.27	0.000
10.	Irrigation contract period (years)	9.34	4.55	14.13	0.000
11.	If have urban market access (1= yes, 0= no)	43.13% (yes)	46.75% (yes)	39.50% (yes)	0.0385
12.	If had a different irrigation contract before (1= yes, 0= no)	44.13% (yes)	70.75% (yes)	17.50% (yes)	0.0000
13.	Mean annual land for all crops (decimals)	80.34	66.87	93.82	0.000
14.	Mean annual yield for all crops (kg)	2184.66	1747.14	2622.18	0.000
15.	If use groundwater (1= yes, 0= no)	80.63% (yes)	78.50% (yes)	82.75% (yes)	0.1287
16.	Coordination (constructed) 1= high coordination, 0= otherwise (low coordination)	43.75% (yes)	70.50% (yes)	17% (yes)	0.000
B	**Outcome variables**				
17.	Irrigation contract type (1= crop contract, 0= otherwise, water contract)	44.63%	68.00%	21.25%	0.000

Source: Author's calculation.

Note: This table reports the descriptive statistics of the selected explanatory/sample balancing variables (Sl. no. 1-16) and the outcome variables (Sl. no. 13). The following Table 5.2 reports other outcome variables. The *p*-value in the last column suggests the significance of the mean difference for each variable between solar and non-solar irrigation user-farmers. Percentage frequencies of "yes" are reported for the discrete binary variables and means are reported for the scale variables. The scatter distribution graphs of scale variables by energy use are also prepared (Figure C.2 in Appendix C).

Table 5. 2 Comparison of means of irrigation-related variables between groups.

Variables	Between solar, diesel and electricity adopters (ANOVA)				Between solar and non-solar adopters (Sample t-test)		
	SS (within group SS)	MS (within group MS)	F	Bartlett's test (χ^2)	Solar (SD)	Non-solar (SD)	*p*-value
Irrigation pump use group (number)	291121.84 (51140.15)	145560.92 (64.16)	2268.51***	297.40***	42.66 (10.43)	24.32 (24.08)	0.000
Irrigation water user group (number)	181165.91 (107222.13)	90582.95 (139.43)	649.66***	212.64***	42.66 (10.44)	30.11 (24.05)	0.000
Distance between land and pump (meters)	7914933.01 (71824056.2)	3957466.50 (90118.01)	43.91***	279.56***	191.57 (282.23)	195.2 (346.67)	0.871
Distance between land and water (meters)	488603842.00 (7678900000)	244301921.00 (9634783.58)	25.36***	491.83***	2298.64 (3827.13)	834.9 (2179.23)	0.000
Mean annual irrigation frequency (days)	11521.79 (588641.762)	5760.90 (738.57)	7.80***	22.61***	25.28 (23.85)	29.51 (30.43)	0.029
Mean annual irrigation time (hours)	656.62 (6388.51)	328.31 (8.01)	40.96***	107.76***	1.17 (2.06)	2.98 (3.42)	0.000
Mean annual irrigation cost (BDT[15])	1905100000.00 (11094000000)	952556389.00 (13919531.2)	68.43***	202.89***	2845.38 (2394.09)	5219.54 (4901.2)	0.000
Mean annual land productivity (kg per decimal)	6057.40 (1412651)	3028.70 (1772.46)	1.71	607.75***	33.14 (55.26)	29.032 (22.2)	0.168
Mean annual percentage of land productivity (% of kg per decimal)	1.73 (48.55)	0.87 (.0609)	14.20***	50.29***	1.88 (0.28)	1.79 (0.2)	0.000

Source: Author's calculation.

Note: This table reports the ANOVA (Equation 5. 3) analysis of the selected outcome variables by irrigation energy and by solar and non-solar adoption. These outcome variables are related to irrigation profiles including management variables, inputs, costs, and crop yields. A significant F statistic in ANOVA shows that an outcome variable varies between the three irrigation energy users. A significant t-statistic shows that an outcome variable differs between solar and non-solar groups. In parentheses, I report errors in ANOVA columns and standard deviations in sample t-test. Bartlett's test assumes that variances are equal for all samples and a significant statistic is that I can reject this hypothesis. Finally in ANOVA and Barlett's test results, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

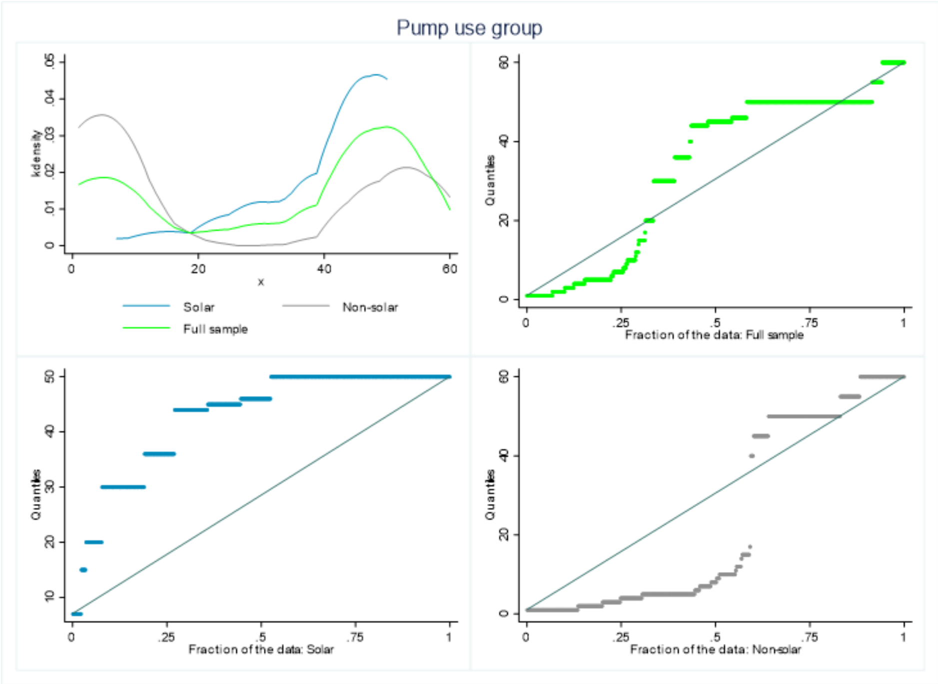
[15] During the time of survey, the average exchange rate was AUD1 = BDT64.633.

Table 5. 3 Skewness, kurtosis and percentile values of outcome variables.

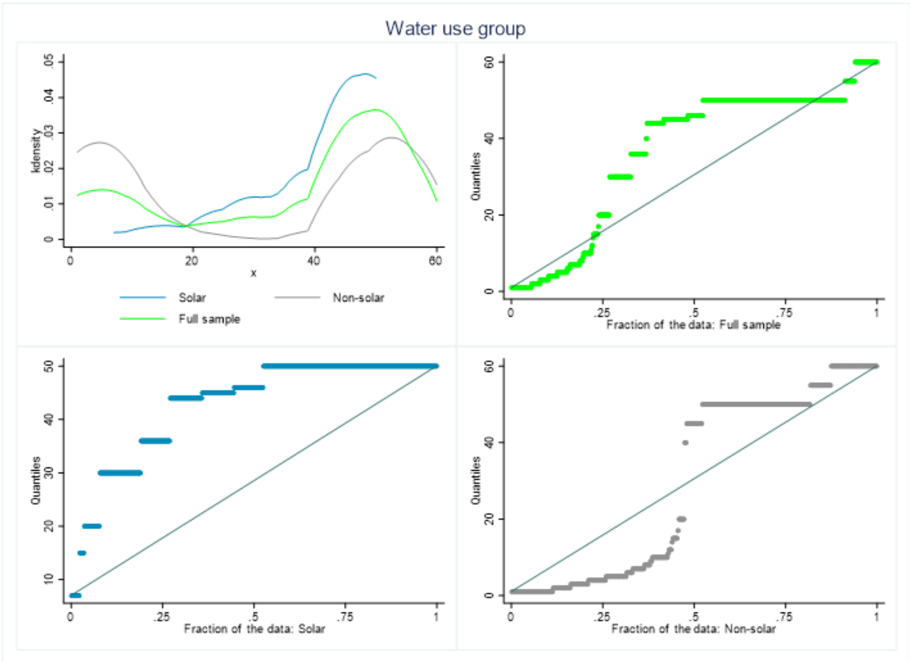
Measures	Solar	Non-solar	Solar	Non-solar	Solar	Non-solar	Solar	Non-solar	Solar	Non-solar	Solar	Non-solar	Solar	Non-solar	Solar	Non-solar
	Pump use group		Water use group		Land to pump distance		Land to water distance		Mean annual irrigation frequency		Mean annual irrigation time		Mean annual irrigation cost		Relative land productivity	
Skewness	-1.62	0.39	-1.62	-0.08	4.42	4.11	1.22	2.91	2.11	2.15	3.317	2.202	1.80	2.502	2.40	2.15
Kurtosis	5.02	1.28	5.02	1.15	33.24	27.06	2.60	9.71	11.99	10.02	17.29	10.04	6.63	14.03	13.83	13.09
Minimum	7	1	7	1	0	0	0	0	1.5	1.33	0	0	300	300	1.18	1.43
p5	20	1	20	1	10	0	10	0	4	3.67	0.07	0.15	641.67	600	1.57	1.57
p25	36	4	36	4	42	5	50	8	7	7	0.15	0.5	1200	1900	1.73	1.66
p50	46	8	46	45	100	63	150	72.5	16.5	18.25	0.31	2	2055	3750	1.83	1.74
p75	50	50	50	50	250	250	950	300	36.5	45.5	1.15	4	3600	7380	1.99	1.88
p95	50	60	50	60	700	800	10000	8000	70.5	85.5	5	10	8225	14025	2.33	2.13
Maximum	50	60	50	60	3000	3000	10000	8000	207	211	17	26	14400	41875	3.71	3.33

Source: Authors' calculations.

Note: This table reports skewness, kurtosis and percentile distributions of outcome variables for solar and non-solar users. A skewness value greater than 1 or less than -1 implies that variable has a highly skewed distribution. Kurtosis value higher than 3 implies that variable's distribution has a longer tail or a larger outliers. Here, 5 levels of data distributions are presented, i.e., 5th, 25th, 50th, 75th and 95th percentiles of each outcome variable in the distribution. Figure 5.1 and Figure 5.2 visualize the results of this table for irrigation groups and lengths.



(5.1.a)



(5.1.b)

Figure 5. 1 Data distributions of irrigation groups by energy use and full sample.
Source: Author's preparations.
Note: This figure presents the density plots and the quantile distributions of irrigations groups using the same pump (Figure 5.1.a) and same water source (Figure 5.1.b). It appears in the density plots for groups that the distribution is bimodal for the non-solar group, hence the full sample shows a bimodal distribution of irrigation group size for both pump and water uses.

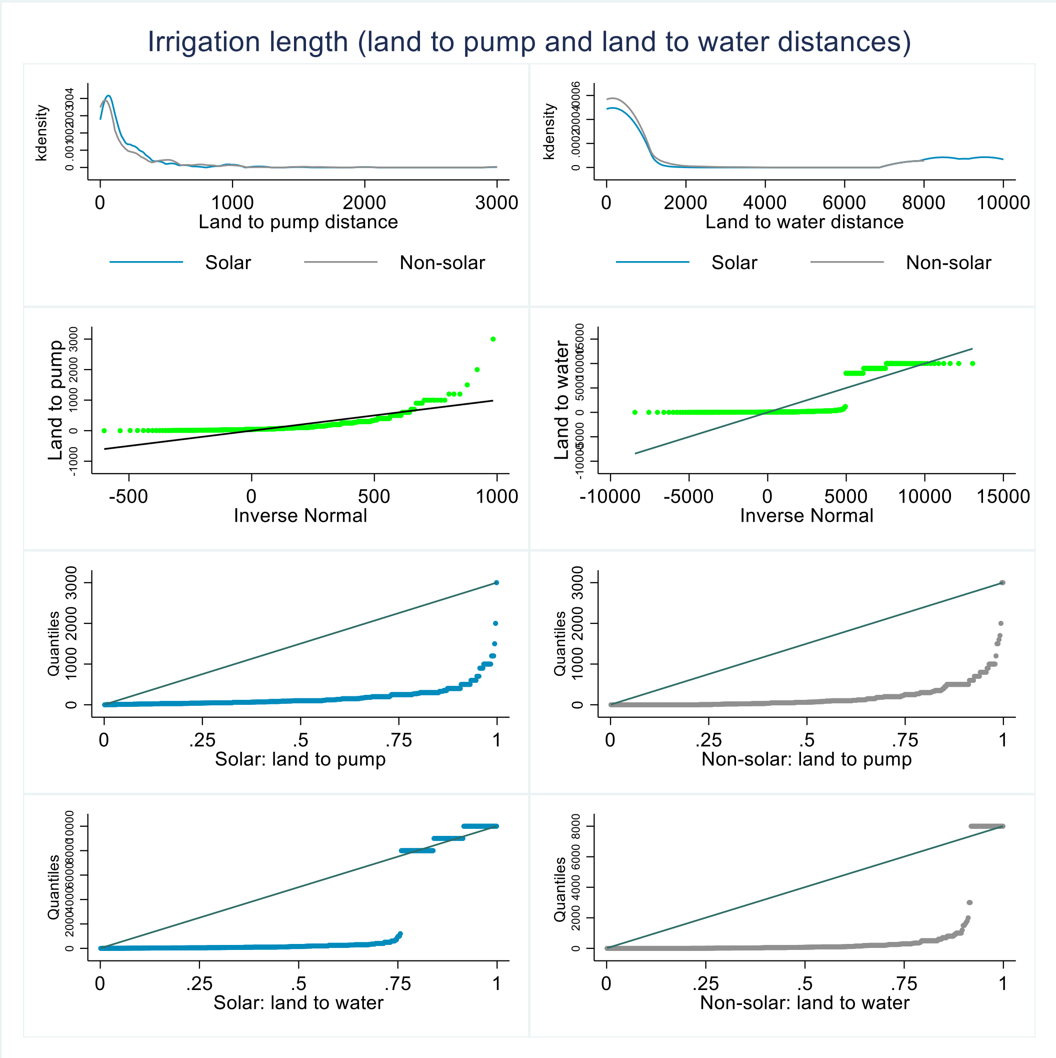


Figure 5. 2 Data distributions of irrigation length by energy use and full sample.
Source: Author's preparations.
Note: This figure presents the density plots and the quantile distributions of irrigations length outcome variables land to pump distance and land to water distance. It shows that the density plots of land to pump distance distributions are skewed and have longer tails. Land to water distance distributions are slightly bimodal. The quantile normal plots show the comparison of data distributions with normal distributions. Plots show that distributions are different.

5.4.2 What causes the choice of contract type

Results in Table 5.4 show that the odds of following a crop contract are higher for solar users than for non-solar users for the full sample and results are similar for high and low adoption areas. Solar users in high adoption areas (8.96 odds ratio) tend to follow a crop contract more than they do in low adoption areas (6.94 odds ratio) compared to non-solar users. Model 5.1 results show that farmers' information accessibility increases the probability of following a crop contract, while credit access reduces its probability. The amount of cultivated land has negative impacts on crop contract probability. There is no impact of income diversification and household size does not influence contract choice for the full sample. However, solar network intensity may or may not have increased dependency at the household level. Farmers with bigger households in high adoption areas and farmers with smaller households in low adoption areas tend to use a crop contract. In a crop contract, payments are made after crop sales. In such a case, there are two possibilities: i) farmers prioritize household maintenance over production cost, and ii) they can do so because of larger cooperation. It is likely that a larger solar diffusion improves cooperation even if farmers struggle with a higher household dependency. Institutional accessibility varies with solar networks and consequently crop contract choice probability. Crop contract users' accessibility to agricultural information is high in high adoption areas, while the same users are less likely to use such information. Crop contract users' credit access is lower in high adoption areas, indicating a larger self-dependence with an increase in solar networks. Urban market access of crop contract users is higher in low adoption areas. Such access indicates a larger crop yield mutually even if solar networks are not extended. Farmers using a crop contract in low adoption areas are more likely to use a water contract previously. Crop contract users in high adoption areas are relatively new users in terms of contract choice.

The probability of solar users' following a crop contract is robust with solar users' institutional accessibility (2.73 odds ratio in Model 5.2), soil type, and land elevation effects (3.88 odds ratio in Model 5.3), and if a crop contract is chosen for economic reasons (3.13 odds ratio in Model 5.4) and water management (3.07 odds ratio in Model 5.6). The difference in margins of solar and non-solar use is the highest in Model 5.1.a (Figure 5.3.c). Energy use has no impact on a crop contract choice with peer pressure. If peers do not impose energy use, cooperation for a contract choice and solar irrigation is voluntary and an individual choice despite structural conditions, e.g., pump or land locations. Farmers who prefer cooperation and find reliable irrigation groups personally, may choose a contract and energy source accordingly. Possibly, for similar reasons, most solar users (68%) choose crop contracts (Table 5.1). In this regard, the estimates of pump capacity invariably show that larger-size pumps tend to operate in a crop contract, i.e., an indication of a larger irrigation group in the study area. The impacts of agricultural information access, contract period, and pump capacity do not vary across models. Solar users receiving agricultural information have the largest impact on crop contract choice with peer pressure, suggesting strong farmer-farmer relations. Since crop contract conceptually requires a higher cooperation level, peer knowledge sharing might have a significant contribution in this case. Involvement in any non-farm activity and household size and access to agricultural credit has no impact on crop contract choice in any of these models. The implication of credit access is important as credit access often facilitates crop management. For example, Delavallade and Godlonton (2023) observed that credit access solves immediate financial issues, increases crop storage use, and that further improves crop sales at a higher price. However, credit uptake in rural areas is often priority-based instead of requirement-based. Farmers may use agricultural credit for non-farm purposes. This pattern could explain the finding of no relation of credit with crop contract choice. Effects of other explanatory variables vary across models. Solar farmers following a different contract (i.e., water contract) previously are less likely to choose a crop contract for economic reasons (odds ratio, 0.5453). This implies that water contract is more sensitive to economic motivations in energy use than crop contract. In a crop contract, farmers using the same pump get irrigation on the same days, thus they use more irrigation time and frequency. In such cases, water use seems to be less efficient. Besides, low irrigation costs would further encourage farmers to be less considerate about future water availability.

Table 5. 4 The estimated probability of using a crop contract.

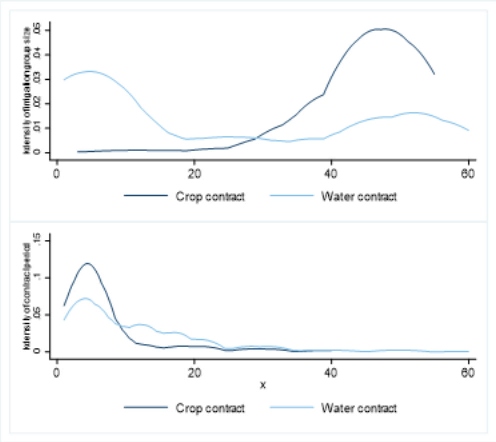
	If using crop contract (1) and otherwise water contract (0)					
	Model 5.1.a Full sample		Model 5.1.b High adoption areas		Model 5.1.c Low adoption areas	
Variables	Odds ratio	Marginal effect	Odds ratio	Marginal effect	Odds ratio	Marginal effect
If use solar irrigation	6.8345*** (1.4298)	0.4395*** (0.0413)	8.1614*** (2.8353)	0.3011*** (0.0551)	6.9456*** (2.8660)	0.3598*** (0.0746)
If involve in any non-farm activity	1.1393 (0.2245)	0.0321 (0.0487)	0.8001 (0.2675)	-0.0302 (0.0433)	1.4797 (0.5740)	0.0709 (0.0661)
Household size	1.0404 (0.0788)	0.0097 (0.0186)	1.3312** (0.1778)	0.0405** (0.0189)	0.6425*** (0.0900)	-0.0846*** (0.0277)
If receives agricultural information	1.2932* (0.2272)	0.0626* (0.0424)	3.9131*** (1.1799)	0.1731*** (0.0368)	0.2877*** (0.1035)	-0.2132*** (0.0566)
If receives agricultural credit	0.6583** (0.1560)	-0.0995** (0.0543)	0.5582 (0.2157)	-0.0730* (0.0429)	0.8729 (0.4431)	-0.0266 (0.1020)
If had a different contract before	1.5046 (0.2887)	0.1001 (0.0469)	0.6206 (0.1873)	-0.0672 (0.0443)	29.4391*** (14.9576)	0.5269*** (0.0514)
If have urban market access	1.0280 (0.1780)	0.0068 (0.0425)	0.8205 (0.2335)	-0.0280 (0.0403)	4.4644*** (1.6880)	0.2543*** (0.0586)
Irrigation contract period	1.0102 (0.0115)	0.0025 (0.0028)	0.8667*** (0.0371)	-0.0202*** (0.0052)	1.0127 (0.0156)	0.0024 (0.0030)
Mean annual cultivated land	0.9979* (0.0012)	-0.0005* (0.0003)	0.9911*** (0.0027)	-0.0013*** (0.0004)	1.0136*** (0.0030)	0.0026*** (0.0006)
Sample size	800		414		386	
Log likelihood ratio	-449.67		-171.85		-141.66	
Prob> chi2	0.0000		0.0000		0.0000	

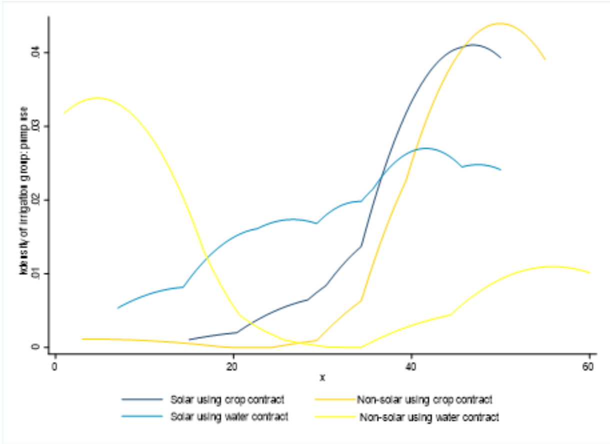
Source: Author's calculations.
Note: This table reports the predicted probabilities (Equation 5. 1) of crop contract use for the full sample and high and low adoption areas. Appendix C presents the relevant ROC of the models. Log-likelihood ratios and the significance of chi-2 tests suggest good model fits. The standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 5. 5 Logit regression results (odds ratios) for the probability of choosing a crop contract.

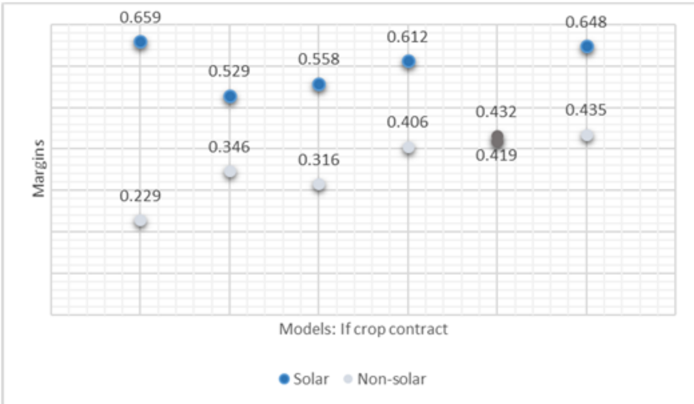
	Model 5.2 Controlled for solar users' institutional accessibility and pump capacity	Model 5.3 Controlled for soil type and land elevations	Model 5.4 crop contract choice for economic reasons	Model 5.5 crop contract choice for peer pressure	Model 5.6 crop contract choice for water management
Variables	Odds ratio	Odds ratio	Odds ratio	Odds ratio	Odds ratio
If use solar irrigation	2.7290*** (0.8992)	3.8824*** (1.3937)	3.1278*** (1.2480)	1.0975 (0.7269)	3.0696*** (1.2816)
If involve in non-farm activity	1.3357 (0.2919)	1.3615 (0.3036)	1.0242 (0.2599)	1.7390 (0.6700)	1.0809 (0.2703)
Household size	1.0254 (0.0849)	1.0490 (0.0888)	1.0483 (0.1070)	0.8646 (0.1273)	1.0183 (0.1041)
If solar receive agricultural credit	0.7944 (0.2562)	0.7957 (0.2610)	1.1510 (0.4268)	0.5034 (0.3332)	1.0179 (0.4281)
If solar receive agricultural information	3.1496*** (0.7719)	2.7322*** (0.6960)	2.7539*** (0.7385)	5.0825*** (2.5759)	2.4121*** (0.7305)
If solar had a different contract before	0.7245 (0.1904)	0.6191* (0.1713)	0.5453** (0.1589)	0.7412 (0.3579)	0.7540 (0.2381)
If have urban market access	1.4229* (0.2763)	1.3014 (0.2645)	1.8441** (0.4370)	1.5812 (0.5412)	1.7877** (0.4384)
Irrigation contract period	1.0432*** (0.0126)	1.0528*** (0.0134)	1.0564*** (0.0193)	1.0477*** (0.0176)	1.0426** (0.0185)
Irrigation pump capacity	1.2324*** (0.0269)	1.2407*** (0.0289)	1.2387*** (0.0336)	1.3777*** (0.0784)	1.1998** (0.0302)
Mean annual cultivated land	0.9953*** (0.0014)	0.9962* (0.0015)	0.9952*** (0.0017)	0.9899*** (0.0030)	0.9973 (0.0019)
If have clay-type cultivated land	--	1.1866 (0.2399)	2.3043*** (0.5112)	0.8332 (0.2674)	1.8055** (0.4249)
If have low elevation land	--	1.8512** (0.4621)			
If have medium elevation land	--	0.5332** (0.1370)			
If have high elevation land	--	0.7995 (0.1684)			
Sample size	800	800	566	311	522
Prob> chi2	0.0000	0.0000	0.0000	0.0000	0.0000
Log likelihood ratio	-388.95	-373.81	-277.49	-134.96	-259.75

Source: Author's calculations.
Note: This table reports the predicted probabilities (odds ratios) of crop contract choice heterogeneity. Appendix C shows the marginal effects and ROC for the models (Equation 5. 1). The following Figure 5.1 visualizes the coefficients and margin comparisons of solar use and its interactions produced from these models. Log likelihood ratios and the significance of chi-2 tests suggest good model fits. The standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

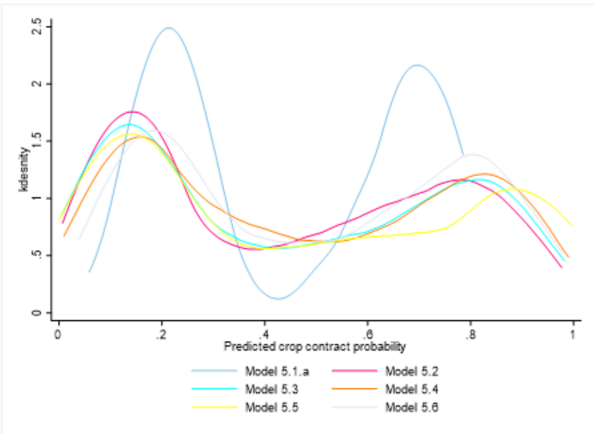




(5.3.a) (5.3.b)



(5.3.c)



(5.3.d)

Figure 5. 3 Sample distributions and model predictions for the probability of crop contract.
Source: Author's preparations.
Note: This figure presents the density plots for two irrigation contract types, margins of solar and non-solar and predicted probability distributions in various logit models. Figure 5.3.a depicts the variation in irrigation group size and contract period between crop and water contracts. Figure 5.3.b further deciphers the group size variation using the same pump for solar and non-solar users in these two contract-types. Figure 5.3.c shows the solar and non-solar margins in predicting the probability of crop contract. Black points in this image indicate no significant margin difference between solar and non-solar users. Finally, 5.3.d presents the kernel density distributions of the predicted probabilities in various logit models. It appears that predictions become less volatile while controlling for the effect of solar users' institutional accessibility, soil and land elevation types and contract choice reasons compared to the first Model 5.1.a.

Low land elevation influences crop contract choice, implying land elevation impacts cooperation level. Clay soil increases the probability of crop contract choice for economic motivations and water management. Both low-land and clay soil have a higher water potential (Alauddin et al., 2020), implying less concern for water supply and irrigation requirements. This may enhance cooperation. Urban market access encourages a crop contract while controlling the effects of institutional accessibility, economic motivations, and water management. However, in land elevation and peer pressure models, urban market access does not influence this type of contract. Farmers sell crops in urban markets if they get a higher yield. The findings suggest that information, economic motivations, and water management can improve yield and consequently facilitate cooperation.

5.4.3 If irrigation group size and length matter

The mean regression results in Table 5.6 show that solar use determines irrigation group size with and without the effects of solar network intensity. The irrigation group size is bigger for solar-using farmers than for non-solar users and this size is even bigger in low adoption areas. The reason perhaps is the pump-size heterogeneity irrespective of solar network intensity. Some low adoption areas have big pumps, while some high adoption areas have small ones[16]. The solar use impact on the water-use group differs between high and low adoption areas. In high adoption areas, a larger group of solar users draw water from the same source, while in low adoption areas, a smaller group of solar users does so. Small households overall and irrespective of network intensity work in big irrigation groups. This implies that if farmers are less concerned about providing for families, they can facilitate on-farm cooperation.

[16] The average solar pump size in high adoption areas is 11.8kwp and the same in low adoption areas is 14.05kwp. The difference is significant at the 1% level.

Agricultural information does not increase irrigation group size and it has no impact in low adoption areas. This indicates that irrigation agricultural extension officers may not monitor group formations and management. The reason can be structural, e.g., locations of pumps and water reservoirs. Crop sales in urban markets positively determine a group size overall and in high adoption areas. However, in low adoption areas, the water-use group size is smaller which sells crops on urban markets and the pump-use group remains unaffected. Clay soil and lowlands invariably impact pump and water groups for the full sample and in high and low adoption areas, the former's impact is negative and the latter has a positive impact. Generally, clay soil holds more moisture and low lands require less irrigation time. Thus, irrigation group size may or may not vary with every soil water-potential feature. Similarly, the solar network may or may not matter in this regard. Bigger size pumps can accommodate and serve a large number of pump users and water users. However, the water group size is bigger in low adoption areas. This happens in surface water source cases. Finally, the mean cultivated land is higher for groups in low adoption areas. One plausible reason for such findings could be the operations of bigger pumps in these areas.

The estimations of irrigation length are largely variable across solar network intensity. A shorter distance between lands and pumps is observed for solar users in low adoption areas. On the other hand, solar users have a longer distance between lands and water sources. However, this distance is longer in high adoption areas than in low adoption areas. In low adoption areas, shorter-length pump users and distant water users receive information. Farmers near pumps and distant water users receive agricultural credit. In high adoption areas, distant pump users have urban market accessibility. However, in low adoption areas, farmers closer to pumps and using water from nearby sources have such accessibility. These findings suggest that irrigation length significantly varies with solar adoption intensity in utilizing information and finance, and yield performance. Irrigation length is smaller for clay soil and lowlands in general and in high adoption areas. Farmers possessing lowlands can draw water from distant sources in low adoption areas. Irrigation pump capacity is not variable across pump use between the full sample and solar network intensity. An important finding is that distant water users have bigger pumps in high adoption areas only. Irrigation length is invariably bigger across higher cultivated lands both in high and low adoption areas.

The overall quantile regression results of irrigation group size and irrigation lengths demonstrate that energy use has a significant impact on these outcomes for various groups of farmers[17]. Solar use impacts are strong across all groups of farmers using the same pump and same water source. The coefficient size increases until the median, implying a stronger positive effect for 50% of the observations. However, the impact is negative at the upper quantile (at the 75th quantile) for any irrigation group. Among other explanatory variables, household size is low at the upper quantiles. Receiving agricultural information has adverse effects at the median for pump use only, suggesting poor dissemination of information in the study area. This impact is plausible because the information content may or may not include solar irrigation. Urban market access and low elevation of land influence irrigation pump use at the lower quantiles and the impacts are relatively small. Market access reduces at the 50th quantile while low elevation impact increases at the 50th quantile using the same pump. Clay soil affects only the upper quantiles of irrigation groups and the effect is negative. Irrigation pump capacity has strong positive impacts at all quantiles. However, the

[17] I test for the equality of impact between quantiles and get significant (at the 1% level) F-statistics for pump use, water use groups. Thus, we can reject the hypothesis that the effects are equal at all quantiles of irrigation groups. In the case of irrigation length of land to pump, we get an insignificant F statistics (0.4639), indicating similar effects at all quantiles. However, land to water distance effects are statistically different at different quantiles, (Prob > F = 0.0054).

impact reduces with quantiles, as the coefficient size gets smaller. This is an important finding in the sense that a small size pump can accommodate a larger irrigation group for any group of farmers, implying a larger pump efficiency in the study area. Mean annual irrigated land influences irrigation group size at the upper quantile (at the 75th quantile). However, the impact is weak as the coefficient size is small (0.0085 for pump use and 0.0070 for water use). Solar and non-solar groups' differences are significant for the predicted quantile estimates against irrigation pump capacity and mean annual cultivated land (Figure 5.7.a). Between irrigation pump and water groups, the impacts of the explanatory variables may vary because of missing outcomes. As solar users are aware of their peers in a group, while non-solar users are not, the missing outcomes are due to the effect of solar energy use. This is an indication of better reciprocity among solar users. Solar users can be wary of water availability and they can estimate the precise requirement.

Table 5. 6 Estimating irrigation groups in a mean regression process.

	Pump use group			Water use group		
	Model 5.7.a Full sample	Model 5.7.b High adoption areas	Model 5.7.c Low adoption areas	Model 5.8.a Full sample	Model 5.8.b High adoption areas	Model 5.8.c Low adoption areas
Variables	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
If use solar irrigation	7.8173***	6.2255***	9.6509***	3.7586***	4.7714***	-6.4501*
	(1.2553)	(1.6314)	(3.4950)	(1.2448)	(1.6534)	(3.4066)
Household size	-1.8014***	-1.7004**	-2.3028***	-1.2847**	-1.9275***	-1.3046*
	(0.4690)	(0.6561)	(0.6899)	(0.5205)	(0.6628)	(0.7820)
If receive agriculture information	-0.8513***	-2.9950*	-3.9236*	-1.8247	-2.8969*	2.7927
	(1.6987)	(1.6473)	(2.0050)	(1.2865)	(1.6501)	(2.1014)
If receive agriculture credit	-3.9027	-0.2709	-1.2233	-1.1942	0.4040	0.7796
	(1.2441)	(2.1291)	(2.7267)	(1.7281)	(2.1071)	(2.6729)
If have urban market access	4.5154***	9.6176***	0.1682	0.8822	9.8376***	-9.1278***
	(1.1963)	(1.6528)	(2.0122)	(1.2792)	(1.7304)	(2.1972)
If have clay-type land	-5.2991***	-4.1727***	-7.4714***	-5.2357***	-5.2385***	-7.1521***
	(1.2461)	(1.5939)	(1.8923)	(1.3168)	(1.6582)	(1.9672)
If have low-elevation land	4.6093***	3.1269*	6.4306***	5.4721***	4.0761**	6.4030***
	(1.3690)	(1.8241)	(2.0155)	(1.4738)	(1.8665)	(2.0723)
Irrigation pump capacity	1.9179***	2.2327***	1.7871***	1.6552***	2.1041***	2.5139***
	(0.1207)	(0.1411)	(0.3624)	(0.1166)	(0.1461)	(0.3588)
Mean annual cultivated land	0.0162	-0.0007	0.0577***	0.0061	-0.0025	0.0304**
	(0.0102)	(0.0117)	(0.0137)	(0.0101)	(0.0119)	(0.0138)
Sample size	800	414	386	772	396	376
F-statistic	66.56***	51.07***	42.53***	31.94***	37.83***	16.65***
VIF	1.18	1.15	1.77	1.17	1.15	1.75

Source: Author's calculations.

Note: This table reports the mean regression (Equation 5. 4) results of irrigation group models for the full sample and high and low adoption areas. Statistically significant F-statistics prove the models' goodness of fit. Appendix D discusses the details of this goodness of fit measure. The standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 5. 7 Estimating irrigation lengths in a mean regression process.

	Land to pump distance			Land to water distance		
	Model 5.9.a Full sample	Model 5.9.b High adoption areas	Model 5.9.c Low adoption areas	Model 5.10.a Full sample	Model 5.10.b High adoption areas	Model 5.10.c Low adoption areas
Variables	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
If use solar irrigation	-8.415	28.331	-172.581***	1951.792***	2018.767***	1562.54**
	(25.719)	(28.175)	(60.355)	(227.891)	(256.922)	(659.587)
Household size	-1.491	-10.959	-0.256	-67.689	-115.944	-156.262
	(11.481)	(10.235)	(17.753)	(90.256)	(100.202)	(134.694)
If receive agriculture information	-102.121***	-45.705	-114.653**	295.717	-303.082	1177.579***
	(26.726)	(27.975)	(44.339)	(222.363)	(252.747)	(414.296)
If receive agriculture credit	-56.901*	-64.284**	-29.198	220.071	771.483**	272.159
	(29.851)	(31.395)	(61.869)	(327.755)	(379.603)	(552.615)
If have urban market access	-9.801	56.182**	-100.857***	-2355.085***	-1295.822***	-3169.338***
	(18.013)	(23.334)	(27.519)	(203.097)	(222.881)	(387.567)
If have clay-type land	-81.671***	-111.465***	-83.384**	-201.967	-755.702***	311.369
	(21.797)	(25.137)	(38.573)	(201.456)	(228.066)	(327.874)
If have low-elevation land	-15.445	-56.754**	15.916	108.563	-691.453**	945.319**
	(24.048)	(28.224)	(42.324)	(224.965)	(270.905)	(385.542)
Irrigation pump capacity	7.391***	10.503***	21.421***	-20.579	38.807***	-10.472
	(1.973)	(2.296)	(4.995)	(14.821)	(12.489)	(57.897)
Mean annual cultivated land	0.881***	0.696***	1.274**	7.878***	7.251***	9.598***
	(0.211)	(0.229)	(0.491)	(1.733)	(1.823)	(3.161)
Sample size	800	414	386	800	414	386
F-statistic	6.40***	7.97***	4.01***	20.97***	8.71***	16.10***
VIF	1.18	1.15	1.77	1.18	1.15	1.77

Source: Author's calculations.

Note: This table reports the mean regression (Equation 5. 4) results of irrigation length models for the full sample and high and low adoption areas. Statistically significant F-statistics prove the models' goodness of fit. Appendix D discusses the details of this goodness of fit measure. The standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

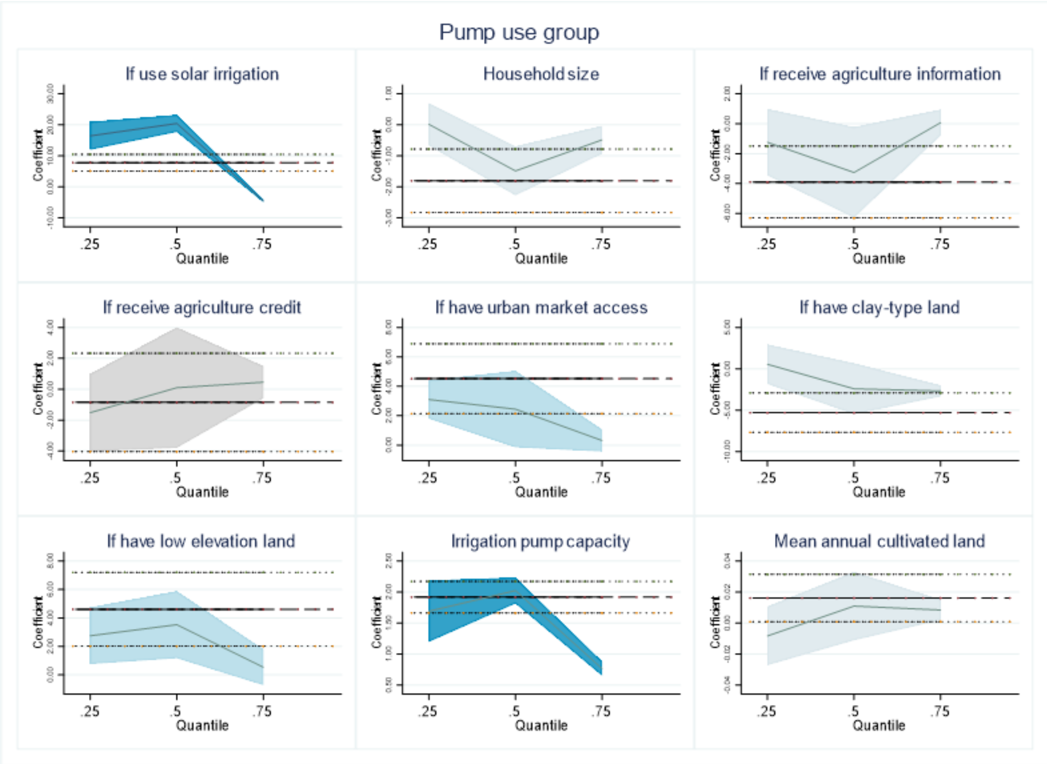
In the case of irrigation lengths, solar use increases the land-to-pump distance at the 25th and 50th quantiles, implying for a maximum of 50% of the observations a solar pump can irrigate at a longer distance. No impact is observed at the upper quantiles. Solar use impacts are stronger in the case of land-to-water source distance, both at lower and upper quantiles (except for the 75th quantile). This additionally indicated solar pumps' greater capacity to channel water from a longer distance for most observations. Among other explanatory variables, household size only negatively impacts land-to-pump distance at the 75th quantile and it has no impact at other quantiles. Agricultural information impact is negative at the lower quantile (25th quantile) and the uppermost quantile (95th quantile) for land-to-pump distance. Farmers at the lower quantile have high access to urban markets if the pump distance is long while the water source distance reduces access for farmers at the upper quantile. I do not elucidate market access for input purchase and harvest sale here. Thus, it cannot confirm if irrigation length hampers water availability and consequently harvest and if it causes market accessibility loss. Clay soil has negative impacts on irrigation lengths at all quantiles. The low elevation of land influences positively only at the lower quantiles. Irrigation pump capacity has an increasingly positive impact on the land-to-pump distance at all quantiles. Its impact on water distance is positive at the 25th and 50th quantiles. Mean annual cultivated land increases irrigation length at the upper quantiles of pump distance, i.e., at the 50th, 75th, and 95th), while it increases with water distance at the lower quantile. The land amount does not affect water distance at the upper quantile. The marginal differences between solar and non-solar farmers for the predicted irrigation length against pump capacity and cultivated land are relatively smaller (Figure 5.7.b).

Table 5. 8 Estimating irrigation groups in a quantile regression process.

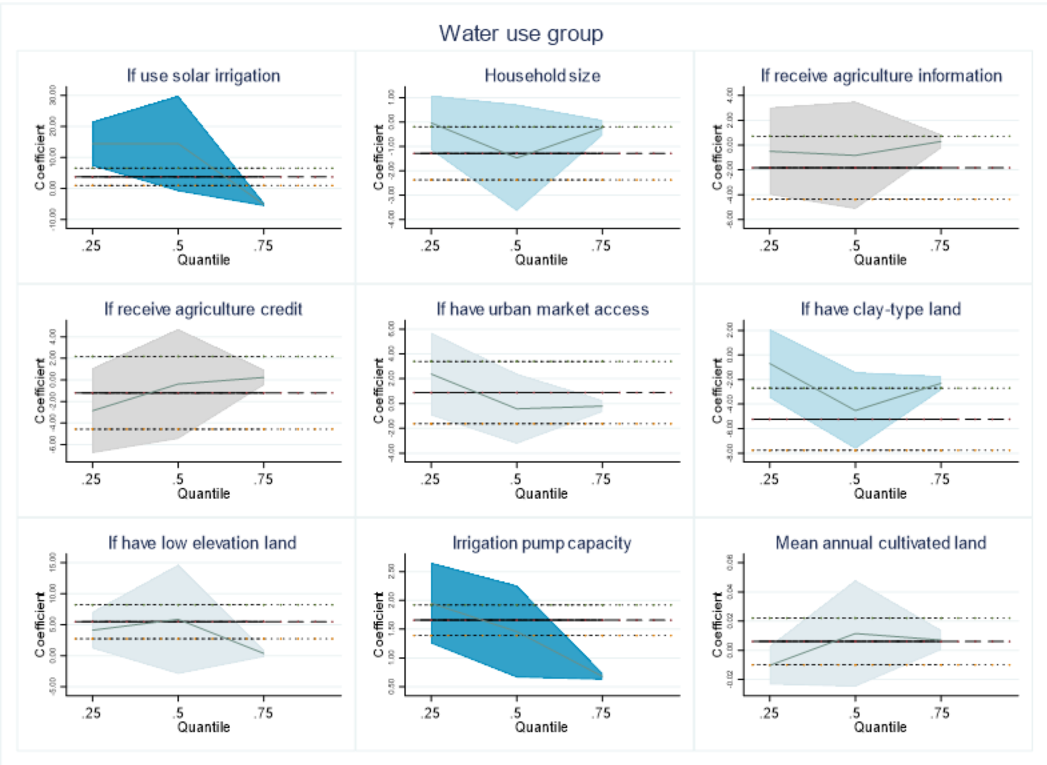
	Model 5.11 Pump use group			Model 5.12 Water use group		
Variables	25th quantile coefficient	50th quantile coefficient	75th quantile coefficient	25th quantile coefficient	50th quantile coefficient	75th quantile coefficient
If use solar irrigation	16.4701***	20.4783***	-4.5111***	14.4233***	14.5212**	-5.0818***
	(3.8354)	(2.6822)	(0.3565)	(2.7593)	(7.2381)	(0.2731)
Household size	0.0185	-1.4832**	-0.4810	-0.0306	-1.4687*	-0.2345**
	(0.3122)	(0.6216)	(0.2939)	(0.4233)	(0.8011)	(0.1002)
If receive agriculture credit	-1.5163	0.1018	0.4554	-2.8551	-0.3795	0.2345
	(1.2605)	(2.0191)	(0.4481)	(1.7527)	(1.9708)	(0.3222)
If receive agriculture information	-1.2395	-3.2607***	0.0779	-0.4950	-0.8257	0.2966
	(0.8789)	(1.1310)	(0.3477)	(1.6412)	(1.3287)	(0.2040)
If have urban market access	3.1036***	2.4510**	0.3164	2.3755*	-0.4231	-0.2105
	(0.8778)	(0.9632)	(0.3062)	(1.3247)	(1.1175)	(0.1718)
If have clay-type land	0.5491	-2.4099	-2.6735***	-0.6969	-4.5307***	-2.3059***
	(1.3710)	(2.06)	(0.4586)	(1.0191)	(1.4733)	(0.2474)
If have low elevation land	2.7489***	3.5282***	0.5387	4.1103**	5.8590	0.3586
	(0.9095)	(1.2415)	(0.7973)	(1.7008)	(4.4999)	(0.3261)
Irrigation pump capacity	1.6914***	2.0246***	0.7671***	1.9520***	1.4578***	0.6797***
	(0.2971)	(0.2155)	(0.0586)	(0.2759)	(0.3443)	(0.0221)
Mean annual cultivated land	-0.0083	0.0109	0.0085**	-0.0103	0.0115	0.0070**
	(0.0083)	(0.0086)	(0.0038)	(0.0098)	(0.0156)	(0.0030)
Sample size	800	800	800	772	772	772
Pseudo R^2	0.4168	0.2746	0.0553	0.3554	0.0658	0.0571

Source: Author's calculations.

Note: This table reports the quantile regression (Equation 5. 5) results of irrigation group models. Table C.1 in Appendix C reports the margins of solar and non-solar users for each quantile. The following figures, Figure 5.6, Figure 5.7 and Figure 5.8 visualize the results of these findings. The pseudo R^2 is a local measure of model fit in median regression, which reduces here gradually with quantiles. Appendix B discusses the details of this goodness of fit measure. The standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.



(5.4.a)



(5.4.b)

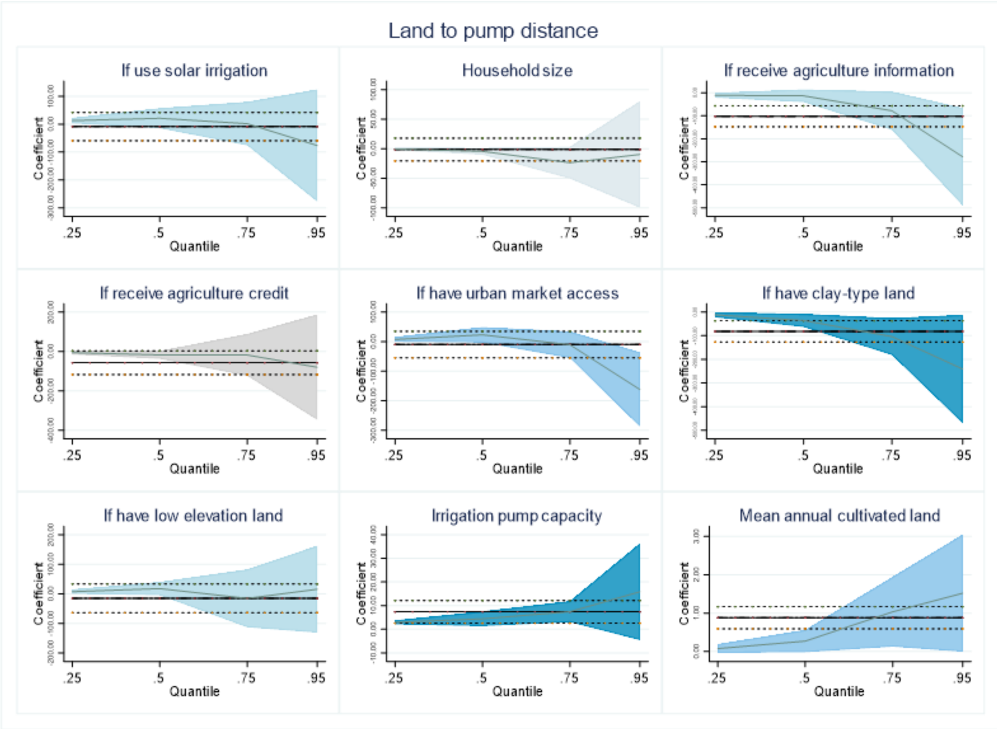
Figure 5. 4 Quantile regression plots of irrigation groups of pump use group and water use.
Source: Author's preparations.
Note: This figure presents the effects of explanatory variables over the quantiles of pump-use group (5.4.a) and water-use group (5.4.b), how the effects differ from mean regression coefficients (solid line) and in terms of confidence intervals around coefficients (dot lines). Grey plots represent insignificant variables, and shades get darker with variables' significance for multiple quantiles.

Table 5. 9 Estimating irrigation lengths in a quantile regression process.

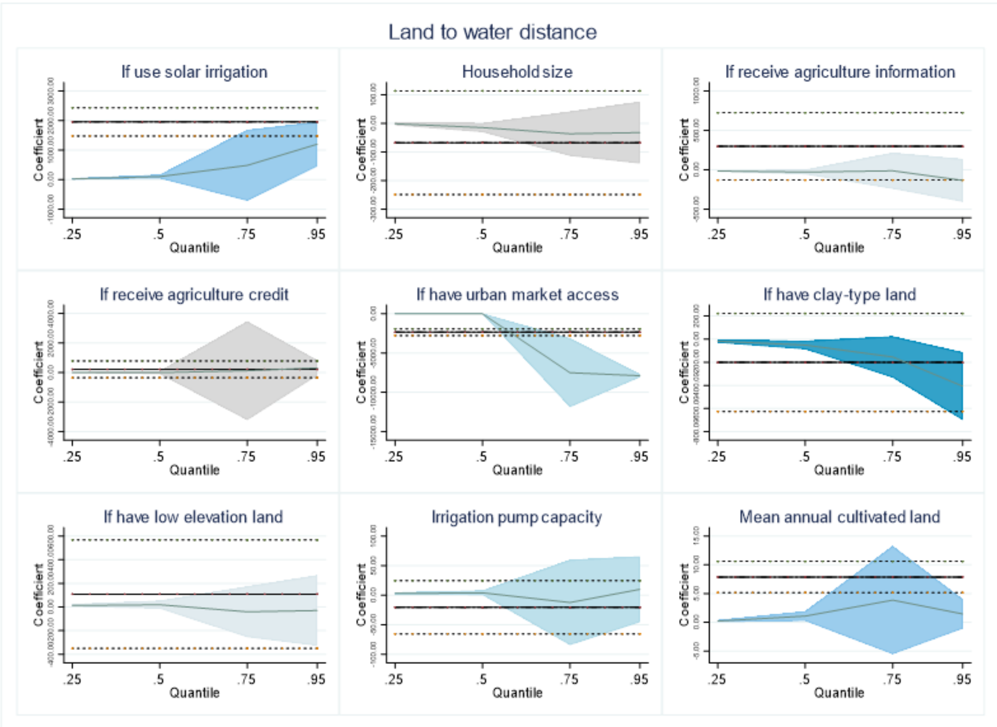
	Model 5.13 Land to pump distance				Model 5.14 Land to water distance			
Variables	25th quantile coefficient	50th quantile coefficient	75th quantile coefficient	95th quantile coefficient	25th quantile coefficient	50th quantile coefficient	75th quantile coefficient	95th quantile coefficient
If use solar	12.848**	21.217***	1.830	-76.632	21.940**	100.50***	478.94	1196.744**
irrigation	(5.974)	(12.204)	(31.845)	(97.266)	(10.673)	(24.261)	(729.882)	(522.205)
	-0.386	-4.653	-23.773**	-9.802	-1.387	-14.858	-36.32	-32.32
Household size	(1.590)	(5.930)	(9.875)	(48.124)	(3.119)	(10.622)	(41.964)	(66.837)
If receive	-5.857	-17.277	-17.444	-79.804	-4.506	-2.174	122.573	317.61
agriculture credit	(5.616)	(16.702)	(51.982)	(91.632)	(6.429)	(39.633)	(1520.783)	(197.875)
If receive agriculture	-11.057**	-13.236	-78.177	-278.475**	-17.152***	-29.586	-13.642	-135.953
information	(4.725)	(12.797)	(53.756)	(139.940)	(6.040)	(19.401)	(194.713)	(106.883)
If have urban	7.691*	23.070**	-10.501	-161.899**	6.242	-22.216	-7507.06***	-7890.68***
market access	(4.018)	(10.521)	(33.952)	(66.893)	(5.017)	(21.543)	(2395.662)	(146.256)
If have clay-type	-11.604**	-35.265***	-103.365***	-240.956***	-17.962***	-51.756*	-154.385*	-406.71*
land	(4.608)	(12.866)	(35.165)	(85.560)	(6.846)	(29.346)	(93.163)	(224.464)
If have low	7.299*	17.401*	-15.448	15.291	12.336***	19.378	-40.858	-29.977
elevation land	(4.094)	(10.524)	(41.166)	(125.702)	(3.683)	(17.368)	(91.986)	(115.528)
Irrigation pump	2.914***	4.451***	7.444***	15.873*	2.813***	3.965*	-12.383	9.903
capacity	(0.816)	(1.477)	(2.054)	(9.590)	(0.878)	(2.066)	(44.153)	(39.807)
Mean annual		0.270**	1.036**	1.521***	0.213**	1.075***	3.859**	1.456
cultivated land	0.076 (0.052)	(0.135)	(0.446)	(0.488)	(0.082)	(0.376)	(1.961)	(1.423)
Pseudo R^2	0.0347	0.0333	0.0651	0.2031	0.0055	0.0087	0.149	0.4098

Source: Author’s calculations.

Note: This table reports the quantile regression (Equation 5. 5) results of irrigation length models. Table C.1 in Appendix C reports the margins of solar and non-solar users for each quantile. Figure 5.5 visualizes the results of these findings. The pseudo R^2 is a local measure of model fit in median regression, which increases here gradually with quantiles. Appendix D discusses the details of this goodness of fit measure. The standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

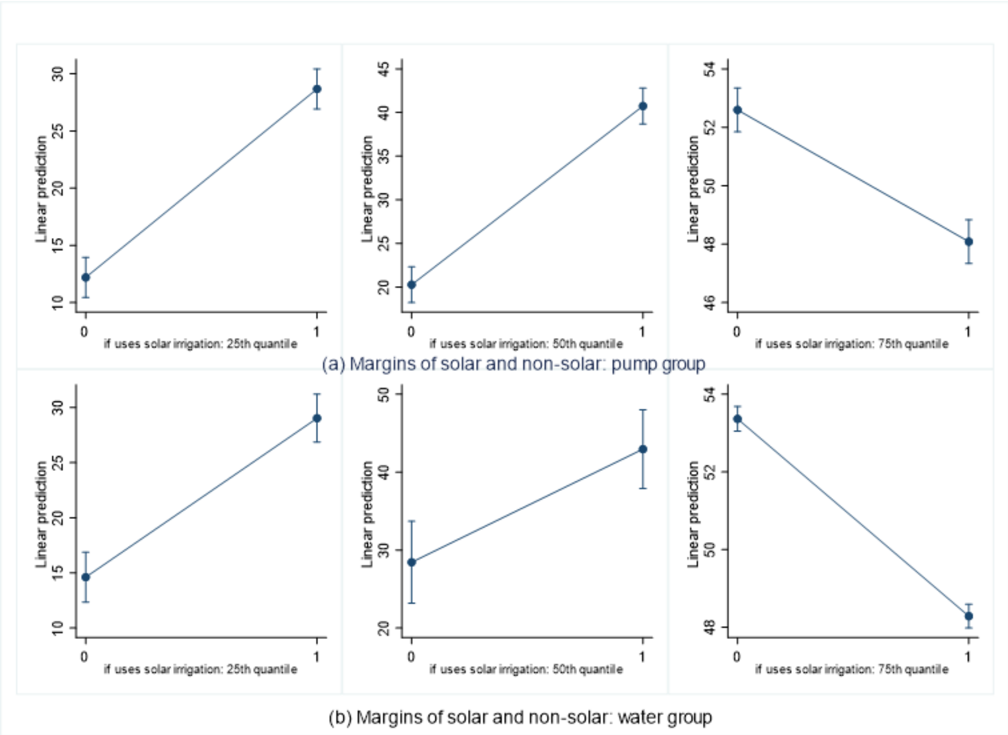


(5.5.a)

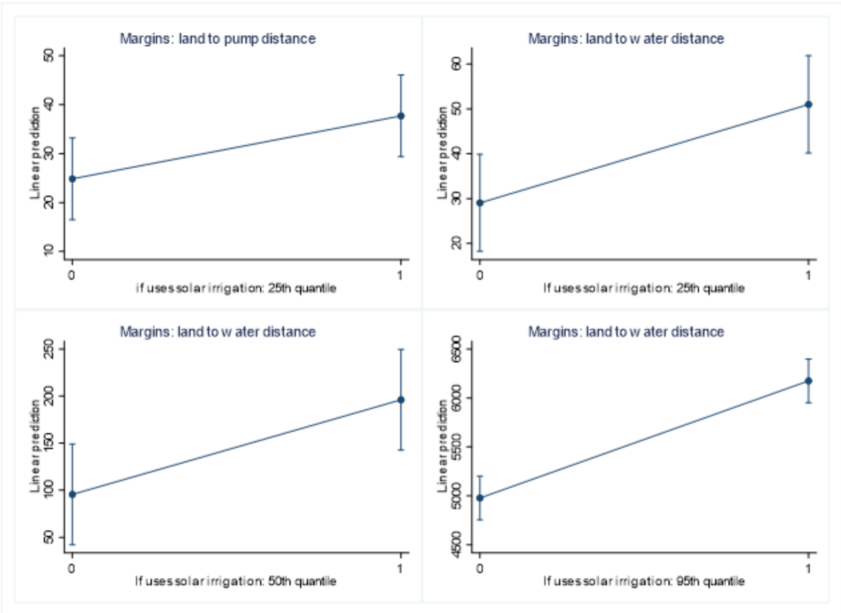


(5.5.b)

Figure 5. 5 Quantile regression plots of irrigation length of pump use and water use.
Source: Author's preparations.
Note: This figure presents the effects of explanatory variables over the quantiles of land to pump distance and land to water distance, how the effects differ from mean regression coefficients (solid line) and in terms of confidence intervals around coefficients (dot lines). Grey plots represent insignificant variables, and shades get darker with variables' significance for multiple quantiles.

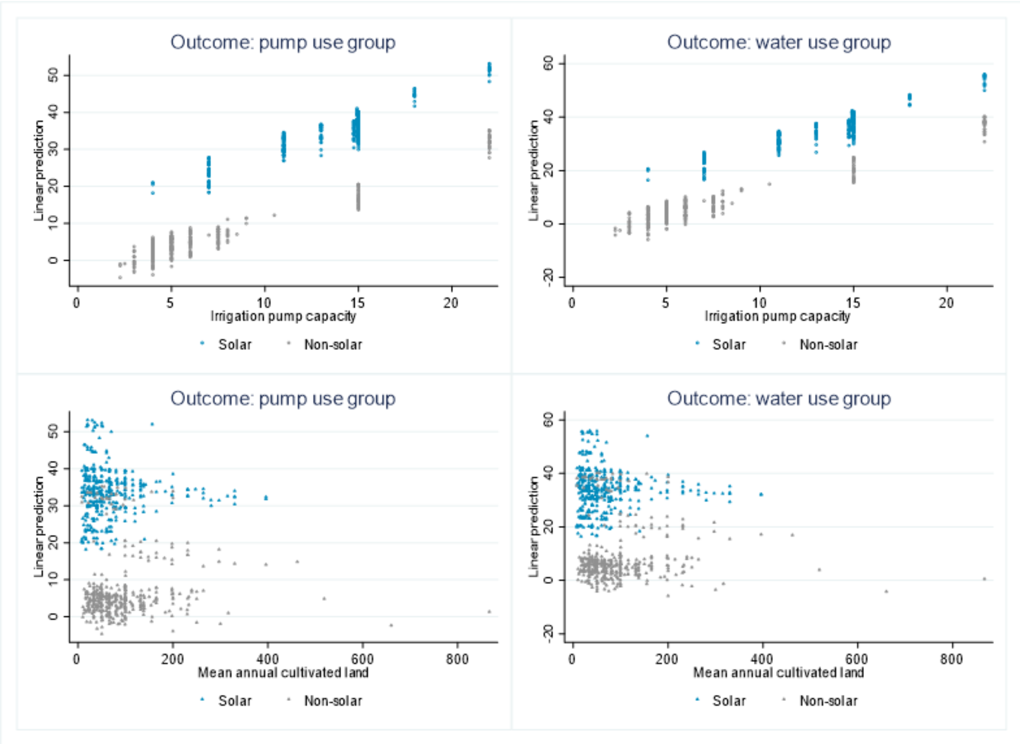


(5.6.a)

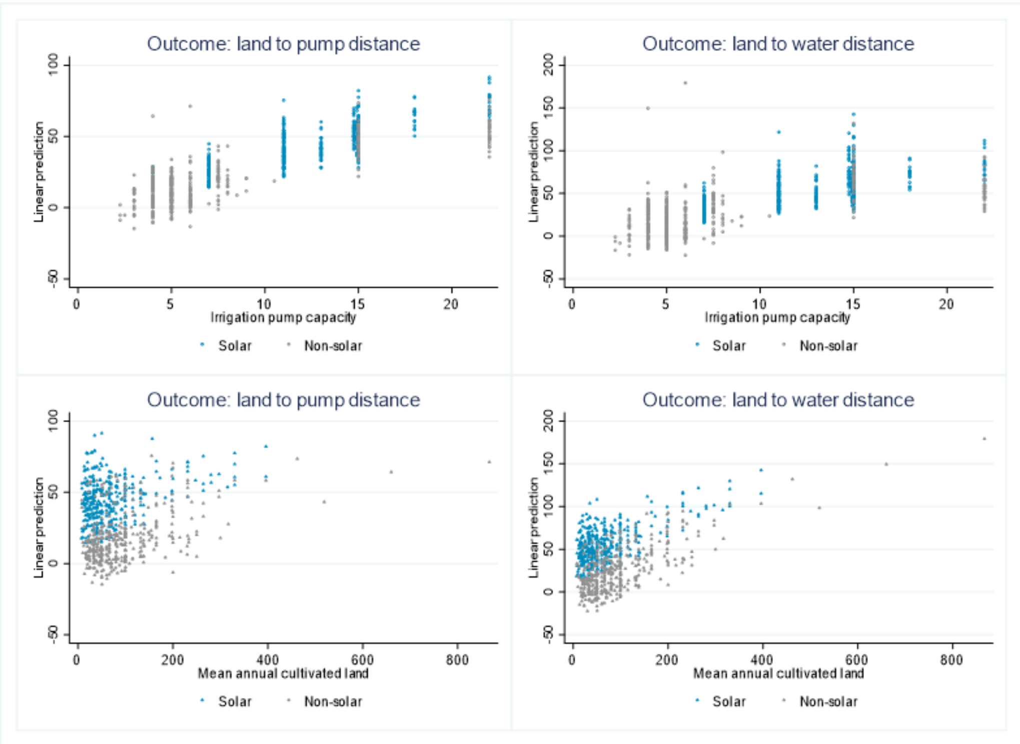


(5.6.b)

Figure 5. 6 Solar and non-solar margins by irrigation groups and irrigation length.
Source: Author’s preparations.
Note: This figure presents the significant margins of solar and non-solar users for a pump use and water use (panel 5.6.a) and for land to pump and land to water distances (panel 5.6.b). Here, only significant quantiles’ results are presented.



(5.7.a)



(5.7.b)

Figure 5. 7 Predicted irrigation groups and lengths for irrigation pump capacity and land amount cultivated.
Source: Author's preparations.
Note: This figure presents the group-wise distributions of the predicted values of pump use group, water use group, land to pump distance and land to water distance against irrigation pump capacity and mean annual cultivated land. It appears that the solar and non-solar differences in the predicted irrigation group outcome are larger than the same in the predicted irrigation length outcomes.

5.4.4 Irrigation efficiency and the significance of coordination

Logit model results of the irrigation profiles did not differ in various models of crop contract prediction. However, in a crop contract, farmers are less considerate about irrigation frequency and time. Crop contracts use higher frequency and timing. Cost can be low depending on the number of users as the contract follows a flat irrigation charge. Thus, there may not be water efficiency, yet economic efficiency improves in a crop contract. The following mean regression results in Table 5.10, Table 5.11, and Table 5.12 show that solar energy has differential impacts on irrigation efficiency indicators. Solar use has no impact on irrigation frequency for the full sample and in high adoption areas. However, solar users do more irrigation in low adoption areas. This indicates two things- i) irrigation is costly and ii) farmers are less frugal in water use, in low solar network. Solar irrigation reduces both time and cost significantly. Irrigation time is 0.67 hours less in solar irrigation and cost reduces by BDT600 for all crops on average annually. The mean annual irrigation cost for all crops for a farmer is BDT4000 approximately. Thus, this impact is substantial, i.e., a 15% reduction in cost. Irrigation time is less in low adoption areas. However, solar network intensity does not impact the cost. Results show that socio-demographic factors may not ensure irrigation's economic efficiency. Non-farm employment increases irrigation timing, and it has no impact on frequency and cost. However, in high adoption areas, irrigation frequency is low if farmers have income diversification. Dyer and Shapiro (2022) similarly found trivial non-farm earnings for households with irrigation treatment. If irrigation is time-consuming, it may engage farmers longer on the field. This affects farm households' welfare gains from irrigation efficiency. In addition to this, household size increases irrigation costs by BDT470. No impact of off-farm activity and bigger households, i.e., a larger dependency on farmer's income indicate low welfare of the study households. In the cases of institutional accessibility, agricultural information, and credit do not influence any of the irrigation efficiency indicators. However, solar network intensity may explain this to some extent.

Table 5. 10 Estimating mean annual irrigation frequency.

	Mean annual irrigation frequency		
	Model 5.15.a Full sample	Model 5.15.b High adoption areas	Model 5.15.c Low adoption areas
Variables	Coefficient	Coefficient	Coefficient
If use solar irrigation	-0.7934 (2.1393)	0.9606 (1.9592)	10.4421** (5.2239)
If involve in non-farm activity	-2.6151 (2.2304)	-5.3101*** (1.8253)	3.4228 (3.6613)
Household size	1.3496 (0.8244)	1.2606* (0.7358)	-0.3308 (1.2905)
If receive agriculture information	3.7792 (2.1673)	5.6702*** (1.6467)	-4.2307 (3.8878)
If receive agriculture credit	-2.5864 (2.6758)	-2.1994 (2.3445)	2.4193 (5.3754)
If have urban market access	7.0566*** (1.9836)	4.1973** (2.1001)	22.8598*** (3.5578)
If have clay-type land	6.8923*** (2.0625)	17.7953*** (1.7936)	-5.5291* (3.2145)
If have low-elevation land	-2.0407 (2.2344)	-7.3883*** (1.9557)	-0.0918 (3.5121)
Irrigation contract period	0.6180*** (0.1803)	0.3505** (0.1768)	0.4854** (0.2325)
Irrigation pump capacity	0.1213 (0.1970)	0.3238* (0.1749)	-1.6024** (0.6189)
Mean annual cultivated land	0.0284 (0.0186)	0.0169 (0.0136)	-0.1096 (0.1173)
Mean annual crop yield	-0.0020*** (0.0005)	-0.0011*** (0.0003)	0.0060 (0.0056)
F-stat	9.36***	12.70***	7.54***
VIF	1.58	1.57	3.22

Source: Author's calculations.

Note: This table reports the mean regression (Equation 5. 4) results of mean annual irrigation frequency for the full sample, and high and low adoption areas. A significant F-statistic confirms a good model fit and VIF (variance inflation factor) lower than 5 indicates that there is no multicolinearity. The standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 5. 11 Estimating mean annual irrigation time.

	Mean annual irrigation time		
	Model 5.16.a Full sample	Model 5.16.b High adoption areas	Model 5.16.c Low adoption areas
Variables	Coefficient	Coefficient	Coefficient
If use solar irrigation	-0.6642*** (0.1611)	-0.0836 (0.2129)	-2.1641*** (0.3114)
If involve in non-farm activity	0.4544** (0.1909)	0.7649*** (0.2857)	-0.1210 (0.2174)
Household size	-0.0730 (0.0750)	0.0732 (0.1182)	-0.1023 (0.0824)
If receive agriculture information	-0.2171 (0.1656)	0.2837 (0.2273)	-0.6912*** (0.2077)
If receive agriculture credit	0.2138 (0.2410)	0.5013 (0.3047)	-0.7263** (0.3231)
If have urban market access	-0.4556*** (0.1575)	-1.0833*** (0.2206)	-0.2985* (0.1703)
If have clay-type land	-0.0941 (0.1483)	-0.5547*** (0.2077)	0.4007** (0.1980)
If have low-elevation land	-0.3145* (0.1712)	-0.3227 (0.2451)	-0.4919** (0.2093)
Irrigation contract period	0.0278** (0.0124)	0.0388** (0.0152)	0.0120 (0.0145)
Irrigation pump capacity	-0.0233 (0.0160)	-0.0595*** (0.0212)	0.0992*** (0.0273)
Mean annual cultivated land	0.0189*** (0.0036)	0.0161*** (0.0043)	0.0382*** (0.0082)
Mean annual crop yield	0.0002*** (0.0001)	0.0003*** (0.0001)	-0.0005 (0.0004)
F-stat	43.44***	47.63***	14.58***
VIF	1.58	1.57	3.22

Source: Author’s calculations.
Note: This table reports the mean regression (Equation 5. 4) results of mean annual irrigation time for the full sample, and high and low adoption areas. A significant F-statistic confirms a good model fit and a low VIF (variance inflation factor) indicates that there is no multicolinearity. The standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

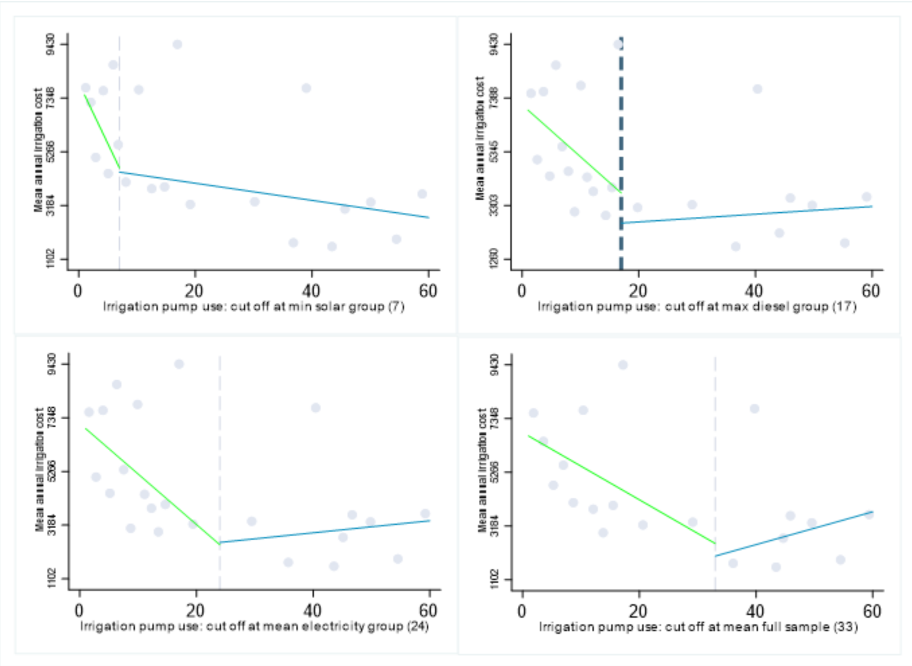
Information increases irrigation numbers in high adoption areas, while timing is less upon receiving information in low adoption areas. Information increases irrigation costs in high adoption areas and low adoption areas have a lower cost with information. Urban market access increases irrigation frequency by 7 days, and it uses less irrigation time (reduces by 0.45 hours). Farmers often use more irrigation to get better yields and this finding suggests that farmers may have similar experiences. Besides, market access increases when their irrigation is input-intensive. Clay soil increases both irrigation frequency and costs. Irrigation frequency is low in high adoption areas with clay soil. Clay soil uses less irrigation time in high adoption areas and low adoption areas require more time. Irrigation cost is low for lowlands in both high and low adoption areas. This study analyses irrigation arrangements' impacts on their efficiency. The irrigation contract period increases all efficiency indicators. A bigger pump improves cost efficiency, by reducing irrigation costs by BDT102. The land amount increases both timing and cost. The mean annual yield reduces timing and cost and the yield's impact is higher in low adoption areas. The impacts of these variables are not substantial.

Table 5. 12 Estimating mean annual irrigation cost.

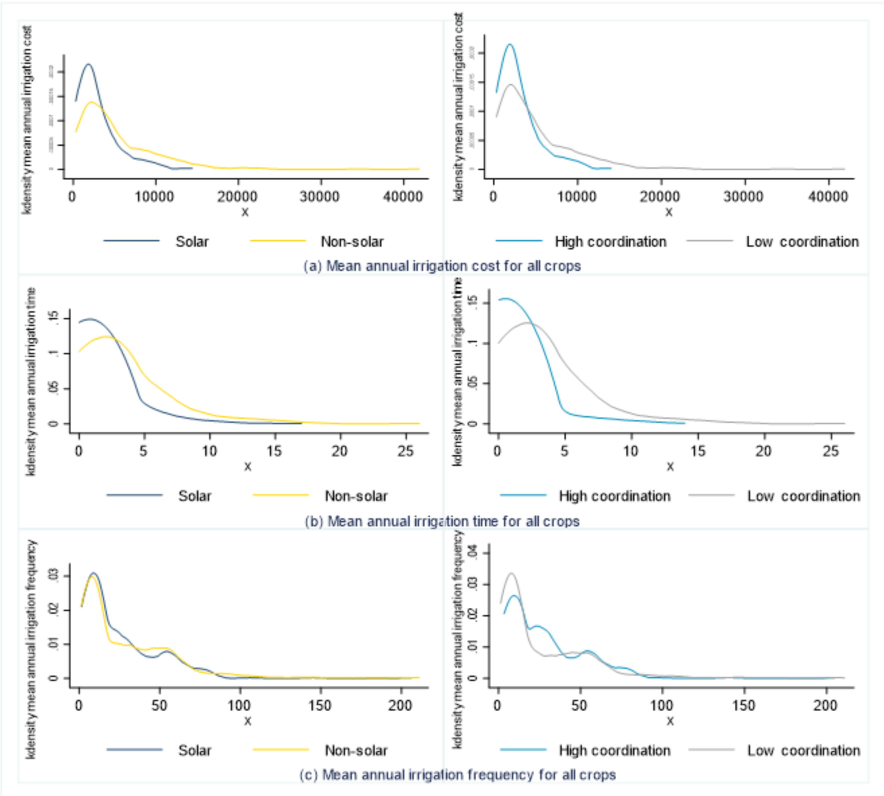
	Mean annual irrigation cost		
	Model 5.17.a	Model 5.17.b	Model 5.17.c
	Full sample	High adoption areas	Low adoption areas
Variables	Coefficient	Coefficient	Coefficient
If use solar irrigation	-599.99***	-344.07	21.11
	(229.88)	(264.06)	(489.40)
If involve in non-farm activity	188.96	306.23	114.29
	(276.80)	(321.88)	(424.78)
Household size	470.06***	253.10**	461.34**
	(132.12)	(102.69)	(181.19)
If receive agriculture information	140.93	696.53***	-635.61**
	(209.89)	(261.18)	(317.93)
If receive agriculture credit	-68.90	-210.37	85.37
	(342.96)	(407.76)	(618.97)
If have urban market access	338.28	-190.66	1906.04***
	(258.19)	(337.36)	(588.15)
If have clay-type land	1315.93***	1220.60***	1245.39***
	(232.53)	(286.21)	(354.04)
If have low-elevation land	-340.98	-712.68**	-710.68**
	(265.55)	(341.93)	(360.52)
Irrigation contract period	61.17***	49.31*	42.29*
	(19.72)	(29.23)	(24.80)
Irrigation pump capacity	-102.87***	-71.86**	-226.27***
	(20.60)	(32.76)	(60.75)
Mean annual cultivated land	35.45***	25.42***	27.16**
	(4.24)	(3.97)	(12.51)
Mean annual crop yield	-0.2977**	-0.1445	0.9813*
	(0.1389)	(0.1144)	(0.5894)
F-stat	22.04***	13.91***	18.16***
VIF	1.58	1.57	3.22

Source: Author's calculations.

Note: This table reports the mean regression (Equation 5. 4) results of mean annual irrigation cost for the full sample, and high and low adoption areas. A significant F-statistic confirms a good model fit and a low VIF (variance inflation factor) indicates that there is no multicolinearity. The standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.



(5.8.a)



(5.8.b)

Figure 5. 8 Different cut-offs for pump use group and coordination variations in irrigation cost, time and frequency.

Source: Author's preparations.

Note: This figure presents the cut-offs for pump use group against mean annual irrigation cost kernel density distributions of irrigation cost, time and frequency by energy use (dark blue for solar and gold for non-solar) and coordination level (bright blue for high coordination and grey for low coordination). The upper panel 5.8.a shows different cut-offs to detect the discontinuity in mean annual irrigation cost 17 in order to construct the coordination variable. The lower panel (5.8.a) shows that despite exhibiting similar distribution patterns, groups differ in the means of irrigation costs, time and frequency.

Table 5. 13 Mean regression results of irrigation efficiency indicators with coordination variable.

Variavles	Model 5.18 Through coordination: Mean annual irrigation time	Model 5.19 Through coordination: Mean annual irrigation cost
	Coefficient	Coefficient
If use solar irrigation	-4.4623*** (0.7008)	-2078.343** (904.069)
If have clay type land	0.2299 (0.1908)	1464.246*** (246.211)
If have low elevation land	-0.3537* (0.1998)	-356.298 (257.730)
If receive agriculture information	-0.1061 (0.1854)	382.557 (239.227)
If receive agriculture credit	0.2181 (0.2458)	-138.905 (317.082)
If have local market access	-0.9727*** (0.1932)	-433.125* (249.285)
Irrigation contract period	-0.0429** (0.0173)	39.031 (22.318)
Irrigation pump capacity	0.1186*** (0.0313)	-53.431 (40.401)
Mean annual cultivated land	0.0164*** (0.0021)	34.246*** (2.709)
Mean annual crop yield	0.0002*** (0.0001)	-0.293*** (0.076)
F-stat	69.42***	55.12***
Under identification LM statistic (chi-2> p-value)	81.294***	81.294***
Weak identification test	44.566	44.566
Over identification test (chi-2> p-value)	10.365***	1.345
Endogeneity test	48.040***	3.496*

Source: Author's calculations.

Note: This table reports the instrumental regression (Equation 5. 8) results of mean annual irrigation time and irrigation cost through coordination. A significant F-statistic (and greater than 10) confirms a good model fit. The standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. A significant under identification test statistic implies that null hypothesis can be rejected. Sago and Yago test uses the size method. Over identification test uses Sargan's statistic. A significant statistic means the null hypothesis of model being not over-identified can be rejected. Finally, significance in the endogeneity test can reject the null hypothesis that instrumented variable may be treated as exogenous. I do not model irrigation frequency with instrumental variable because of a low value of F-statistic.

These findings suggest that irrigation infrastructure may not be largely efficient except for energy use. It may not confirm a connection between irrigation efficiency, contract arrangements and energy choice. So, I look at the data distributions of irrigation profiles and observe if the energy choice of an irrigation group and contract-change history can jointly influence in this matter. Figure 5.8.b shows that data distributions of irrigation efficiency indicators are highly skewed and most values lie around the left tail and right tails are longer. It is also evident in Table 5.3 that 50% of the observations have a higher distribution in these categories. Figure 5.8.a shows that there is a sharp discontinuity in mean annual irrigation cost distribution at the cut-off of the maximum user number (17) for diesel irrigation. Irrigation cost differs between groups before and after this cut-off point. In the full sample, 43.75% of the farmers belong to the high coordination category. Groups differ significantly (at the 1% level) in the constructed coordination, 70.5% of solar users and 17% of non-solar users belong to the high coordination category (Table 5.1). The mean regression estimates with instrumental variables for solar irrigation show that solar irrigation use reduces irrigation time by 4.4 hours and cost by BDT2074 approximately. These estimates are quite impactful compared to the estimates in the mean regression processes without controlling for coordination. However, the impacts of other factors do not vary much. That is an indication of a high coordination impact of solar irrigation on economic efficiency. Similar positive contribution of cooperation in agriculture or water use is observed in the literature (e.g., Barry and Rousselière, 2021; Meinzen-Dick et al., 2018). The instrumental variable for solar has sufficient explanatory power to predict the outcome variables (a significant under-identification test statistic, 81.294 at the 1% level). None of the maximal critical values in the size method of Stock and Yago exceeds the Wald statistic[18], indicating a larger strength of the instrumental variable. Finally, according to the endogeneity test, the null hypothesis that solar use may be exogenous can be rejected. The predicted density curves of irrigation time and cost also differ between solar and non-solar groups with and without coordination (Figure 5.9).

The economic efficiency of irrigation is explained in terms of relative change in the mean annual land productivity (Table 5.14). The mean regression results show that solar irrigation use increases land productivity by 7.6% (at the 5% significance level). Solar users in high adoption areas experience a higher productivity of 18%

[18] The Wald statistic 44.56 is greater than 19.93 (at the 10% maximal IV size), 11.59 (at the 15% maximal IV size), 8.75 (at the 20% maximal IV size), and 7.25 (at the 25% maximal IV size).

approximately, while solar use has no impact in low adoption areas. The impact is similar for solar use receiving agricultural information (7.2% for the full sample and 9.81% in high adoption areas at the 5% significance level). Local market access and clay land also have positive impacts on land productivity. In this estimation, I use local market access instead of the urban market to observe if irrigation efficiency is sensitive to market type[19].

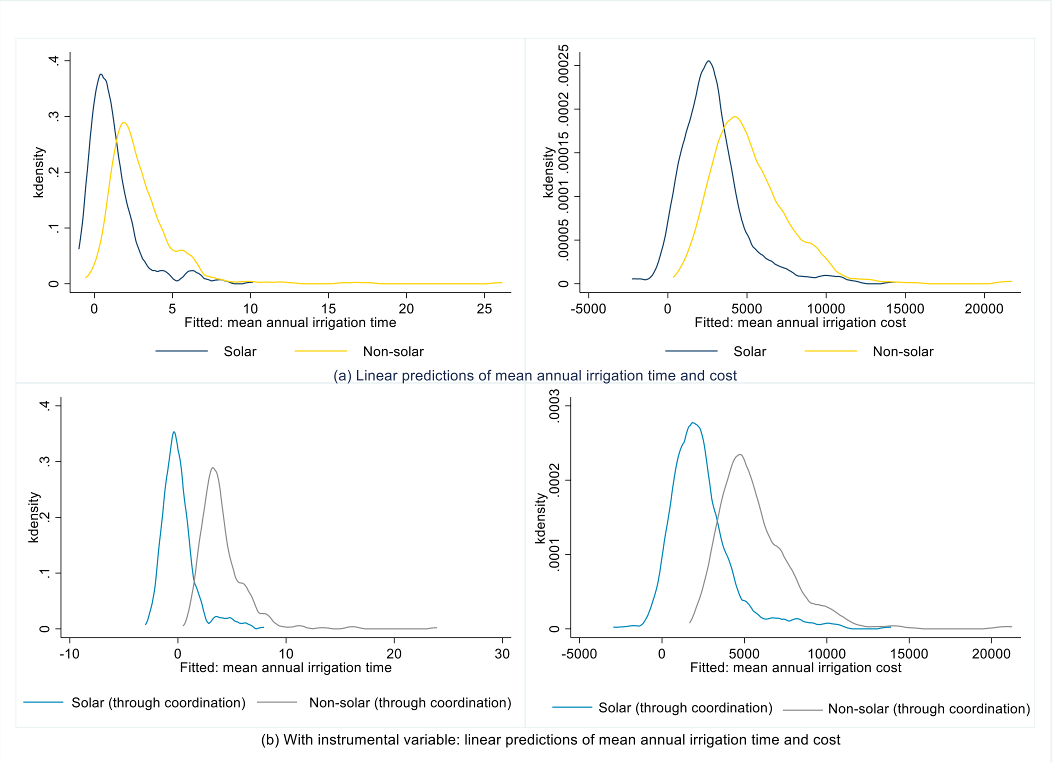


Figure 5. 9 Density distributions of the predicted irrigation time and cost with and without instrumental variable.
Source: Author's preparations.
Note: This figure presents the kernel density distributions of the predicted values of mean annual irrigation time and mean annual irrigation cost for solar and non-solar groups, without instrumental variable (panel a) and with instrumental variable (panel b). Instrumental variable inclusion shows a larger group differences.

[19] For trial, I have used a different model including farmers' urban market accessibility. In this estimation, urban market has no impact on irrigation cost or irrigation frequency through coordination. This model is not included in this thesis.

Irrigation's productive efficiency is substantial in the study area. A 1% increase in mean annual irrigation cost reduces 13.92% of mean annual land productivity. Among the constraints, low elevation, solar users' contract change history, contract period, and pump capacity adversely affect land productivity change. Solar users' contract change history reduces land productivity by 13.97% for the full sample and 26.16% in high adoption areas. The following Figure 5.10 also shows that the results are volatile for various groups. The impacts of the contract period and pump capacity are sufficiently low.

Table 5. 14 Mean regression results of proportionate change in land productivity.

	Proportion change in mean annual land productivity		
	Model 5.20.a Full sample	Model 5.20.b High adoption areas	Model 5.20.c Low adoption areas
Variables	Coefficient	Coefficient	Coefficient
If use solar irrigation	0.0760** (0.0367)	0.1847*** (0.0654)	0.0429 (0.0374)
q2_hh_size	0.0023 (0.0085)	-0.0018 (0.0163)	0.0079 (0.0056)
If solar user receive agriculture information	0.0726** (0.0296)	0.0981** (0.0497)	0.0115 (0.0231)
If solar user receive agriculture credit	-0.0057 (0.0438)	-0.0313 (0.0705)	-0.0093 (0.0288)
If solar user had a different contract previously	-0.1397*** (0.0376)	-0.2616*** (0.0624)	0.0129 (0.0253)
If have clay-type land	0.0354** (0.0156)	-0.0308 (0.0295)	0.0930*** (0.0145)
If have low-elevation land	-0.0468** (0.0207)	0.0344 (0.0249)	0.0420*** (0.0159)
If have urban market access	0.0327** (0.0141)	-0.0539 (0.0350)	-0.0479*** (0.0166)
Irrigation contract period	-0.0013* (0.0007)	-0.0016 (0.0016)	-0.0013** (0.0006)
Irrigation pump capacity	-0.0036** (0.0015)	-0.0058** (0.0024)	-0.0108*** (0.0026)
Change in mean annual irrigation cost	-0.1392*** (0.0096)	-0.1329*** (0.0173)	-0.1401*** (0.0086)
F-stat	36.23***	16.48***	33.34***
VIF	1.71	1.71	2.21

Source: Author's calculations.

Note: This table reports the mean regression (Equation 5. 4) results of proportionate change in mean annual land productivity for the full sample, and high and low adoption areas. A significant F-statistic confirms a good model fit and a low VIF (variance inflation factor) indicates that there is no multicolinearity. The standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

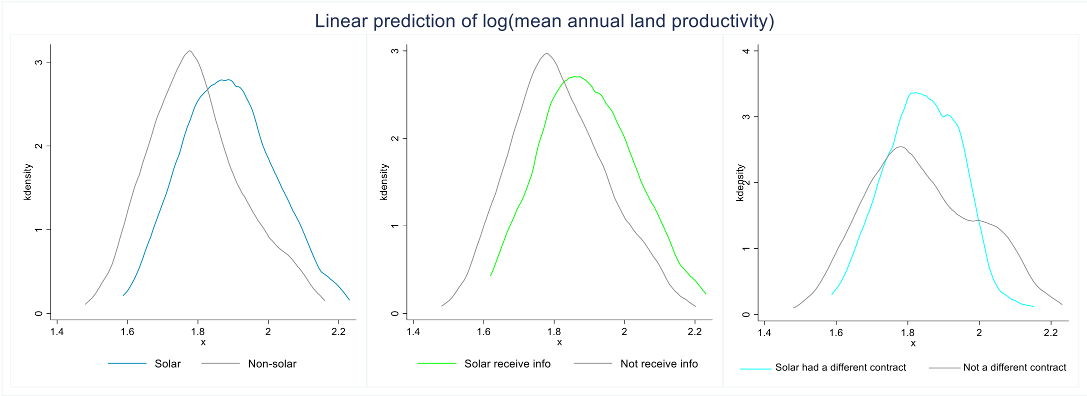


Figure 5. 10 Density distributions of the predicted land productivity.
Source: Author's preparations.
Note: This figure presents the kernel density distributions of the predicted values of relative change in mean annual land productivity for solar and non-solar groups, by energy groups and receiving agriculture info and by energy groups and previously a different contract experience.

5.4.5 Robustness and heterogeneity tests results

I test for the robustness of the above findings of instrumented solar use impact on mean annual irrigation frequency, irrigation time, and irrigation cost (Table 5.15). I re-estimate the outcomes in three different processes. These re-estimation regression processes estimate the average treatment effect of solar irrigation use on the outcome variables, i.e., $y_i = a_0 + solaruseATE + X\beta + \mu_0$ and $ATE = E(y_1 - y_0)|solaruse, X.$ Here, X is the set of explanatory variables. Firstly, two-step regression processes predict the solar use on coordination variable controlled for other variables in a probit model and then employ the OLS model to estimate the scale outcomes on solar use taking value 1 controlled for other explanatory variables. Secondly, the regression process estimated by probit and two-stage least squares uses the probit model to predict solar use on coordination variables controlled for other variables, runs an OLS on solar use, and gets fitted values. Another OLS model predicts outcome variables on the fitted values of the second stage and other explanatory variables. Finally, the Heckman two-step model uses observed and unobserved heterogeneity and finds consistent and efficient estimates of outcome variables. For heterogeneity of irrigation efficiency indicators, I estimate irrigation efficiency indicators- i) for crop contract users and water contract users separately, ii) across farm equipment ownerships, and iii) irrigation water sources (Table 5.16).

For robustness, the average treatment effect of solar irrigation use through coordination reduces irrigation frequency, timing, and cost in all regression processes. In various cohorts' analyses, irrigation frequency differs between groups for crop contract users, farmers using government-owned groups, and irrigation water sources. Notably, frequency increases if farmers use government-owned pumps, suggesting low institutional monitoring and a larger possibility of water wastage. The mean annual irrigation timing is significantly different between solar and non-solar users across all groups of farmers. The solar group uses less time in a water contract, while government-owned pumps operate and use groundwater. In these cases, farmers probably are more concerned about irrigation charges due to local water availability. Another significant finding in this regard is that groundwater use in solar energy is less expensive, indicating a higher solar efficiency for water-scarce areas. Solar users' mean annual irrigation cost is significantly higher than non-solar users for government-owned pumps and for surface water use. This finding is due to the inclusion of electricity users only in the non-solar category. Change in mean annual land productivity is higher for solar users in a crop contract (12% difference), farmers owning any irrigation equipment (30% difference), surface water use (14% difference), and groundwater use (4% difference).

Table 5. 15 Re-estimation of irrigation efficiency outcomes with instrumental variable.

	Mean annual irrigation frequency through coordination		
Variable	Probit and OLS	Probit and 2SLS	Heckit
ATE of solar irrigation use		-15.96	29.16***
Predicted probability of solar use	37.11***		
F-statistic	11.33***	5.24***	8.99***
	Mean annual irrigation time through coordination		
Variable	Probit and OLS	Probit and 2SLS	Heckit
ATE of solar irrigation use		-1.77*	-4.64***
Predicted probability of solar use	-5.09***		
F-statistic	80.18***	39.53***	74.24***
	Mean annual irrigation cost through coordination		
Variable	Probit and OLS	Probit and 2SLS	Heckit
ATE of solar irrigation use		-5223.63***	-577.09
Predicted probability of solar use	-717.45		
F-statistic	51.65***	27.96***	39.75***

Source: Author's calculations.

Note: This table reports the instrumental variable regression results of mean annual irrigation frequency, mean annual irrigation time and mean annual irrigation cost. I test all irrigation frequency here to confirm if F statistic in this process is less than 10. The estimates are average treatment effect of solar use through coordination on the outcome variables. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

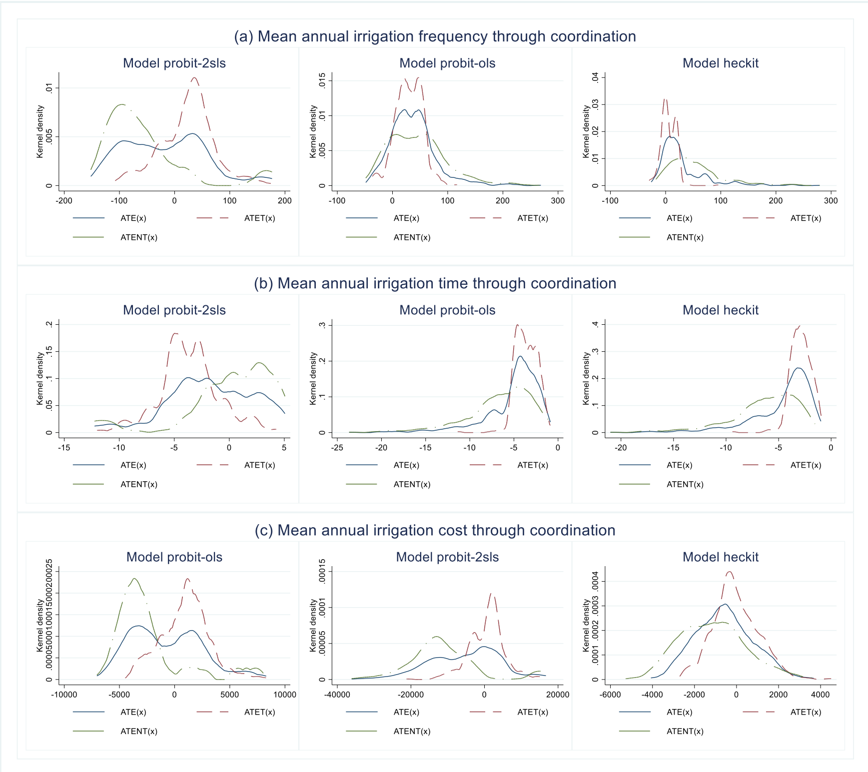


Figure 5. 11 Density distributions of the predicted irrigation efficiency indicators in various regression processes.

Source: Author's preparations.

Note: This figure presents the density distributions of the predicted values of mean annual irrigation frequency, mean annual irrigation time and mean annual irrigation cost. All distributions, average treatment effect (ATE), average treatment effect on the treated (ATET) and average treatment effect on the non-treated (ATENT) show different distributions in all processes.

Table 5. 16 Heterogeneity test of irrigation efficiency indicators.

Crop contract users	**Solar**	**Non-solar**	**Difference**
Mean annual irrigation frequency	25.23 (1.90)	47.50 (4.58)	-22.26*** (5.76)
Mean annual irrigation time	1.86 (0.15)	0.71 (0.37)	1.16** (0.46)
Mean annual irrigation cost	3249.54 (114.96)	3401.89 (277.29)	-152.36 (348.65)
Mean annual change in land productivity	1.90 (0.02)	1.78 (0.04)	0.12** (0.05)
Sample size		**357**	
Water contract users	**Solar**	**Non-solar**	**Difference**
Mean annual irrigation frequency	24.96 (3.73)	24.83 (1.78)	0.13 (5.05)
Mean annual irrigation time	1.91 (0.31)	2.71 (0.15)	-0.81* (0.41)
Mean annual irrigation cost	3857.04 (618.71)	4949.95 (295.25)	-1092.91 (836.86)
Mean annual change in land productivity	1.84 (0.03)	1.81 (0.01)	0.04 (0.04)
Sample size		**443**	
Farmers who own irrigation equipment (functioning or not)	**Solar**	**Non-solar**	**Difference**
Mean annual irrigation frequency	11.22 (12.88)	30.67 (1.92)	-19.45 (14.21)
Mean annual irrigation time	5.01 (0.99)	2.79 (0.15)	2.22** (1.09)
Mean annual irrigation cost	4045.14 (1833.83)	5132.50 (273.55)	-1087.36 (2023.52)
Mean annual change in land productivity	2.08 (0.09)	1.79 (0.01)	0.30*** (0.09)
Sample size		**396**	
Farmers using government owned pump	**Solar**	**Non-solar**	**Difference**
Mean annual irrigation frequency	14.59 (0.63)	-1.30 (2.23)	15.89*** (2.77)
Mean annual irrigation time	1.89 (0.24)	3.83 (0.86)	-1.94* (1.06)
Mean annual irrigation cost	3351.08 (148.72)	562.23 (529.83)	2788.85*** (656.50)
Mean annual change in land productivity	1.88 (0.05)	1.67 (0.17)	0.22 (0.21)
Sample size		**165**	
Farmers using surface water	**Solar**	**Non-solar**	**Difference**
Mean annual irrigation frequency	14.16 (1.27)	7.84 (1.66)	6.31** (2.79)
Mean annual irrigation time	2.43 (0.295)	1.74 (0.356)	0.691 (0.615)
Mean annual irrigation cost	3705.68 (323.66)	2342.94 (304.74)	1362.73** (288.14)
Mean annual change in land productivity	1.92 (0.073)	1.58 (0.072)	0.343** (0.143)
Sample size		**149**	
Farmers using groundwater	**Solar**	**Non-solar**	**Difference**
Mean annual irrigation frequency	31.59 (1.76)	30.83 (1.57)	0.757 (2.52)
Mean annual irrigation time	1.73 (0.132)	2.36 (0.117)	-.633*** (0.189)
Mean annual irrigation cost	4019.16 (152.12)	4455.57 (198.26)	-436.41* (254.51)
Mean annual change in land productivity	1.91 (0.026)	1.81 (0.018)	0.114*** (0.043)
Sample size		**645**	

Source: Author’s calculations.
Note: This table reports the mean regression results of mean annual irrigation frequency, mean annual irrigation time, mean annual irrigation cost, and mean annual change in land productivity for various cohorts of farmers. Farmers who own a pump The standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.5 Conclusion and policy implications

This chapter evaluates cooperation indicators of an irrigation setting conditional on solar irrigation use. Using the natural experiment design and a field survey of 800 farming households, this study compares cooperation indicators for solar and non-solar irrigation users. The first indicator, contract type is significantly different between solar and non-solar users. Solar users are more likely to follow a crop contract. Crop contract choice matters for economic reasons and water management. The second cooperation outcome, irrigation group size differs across farmers. Solar energy users irrigate in larger groups (for pump use and water use) at the median (50% of the observations). Solar use improves the third cooperation indicator, irrigation lengths of a pump from land and water source to the land. Energy use does not affect pump distance at the upper quantiles and water source distance at the 0.75 quantiles. Irrigation's productive and economic efficiency is the fourth outcome indicator that gives a rationale for cooperation. Irrigation timing and cost reduction in solar irrigation. While instrumenting solar with the constructed coordination (an interaction of group size and contract change history), impacts are stronger, suggesting solar irrigations' economic efficiency due to coordination. Land productivity also improves in solar irrigation use.

The takeaway is that long-term reciprocity and management efficiency will increase cooperation for any climate-smart technology. From robustness and heterogeneity tests, this study draws a few policy implications. Farmers using government-owned pumps irrigate for a higher number of days (despite shorter timing). Extension services could use stringent monitoring of water requirements and water use. Less irrigation timing is observed in a water contract and low adoption areas. Crop contract uses a longer irrigation time in solar irrigation. Therefore, to improve the schedule and ensure frugal water use in a crop contract, a progressive charge could be useful instead of a flat rate. The mean annual irrigation cost remains high in extended solar adoption areas and for government owned pumps. This may be due to the smaller capacity of these pumps. Thus, pumps' productive capacity increase should be an additional priority with solar irrigation upscaling. Energy use has differential impacts on irrigation efficiency indicators for groundwater and surface water uses. Thus, it is required to plan a holistic approach to water-energy efficiency depending on the local water scenario. This study also found that solar farmers' ownership of irrigation equipment improves land productivity more than that of non-solar users. This finding can be contaminated as solar users do not use solar energy on personally owned pumps. Solar users in this cohort can own a pump, which was not functional during the study period. However, institutions including private and public projects should plan relaxed leasing conditions for pump use and discuss future ownership possibilities. This study also found significant impacts of irrigation pump capacity, use of agricultural information, market access, soil quality, land elevations, and contract period on various cooperation indicators. Nevertheless, type and content of information is not evaluated and credit accessibility is not satisfactory in the study area. The agricultural extension module can include cooperation benefits in greater irrigation efficiency and monitoring can confirm this during cultivation periods. Instead of personal agricultural loans, irrigation groups could collectively utilize credits. Such offers will increase joint liability and hence can ensure productive uses.

Appendix C
Additional graphs and tables for irrigation cooperation

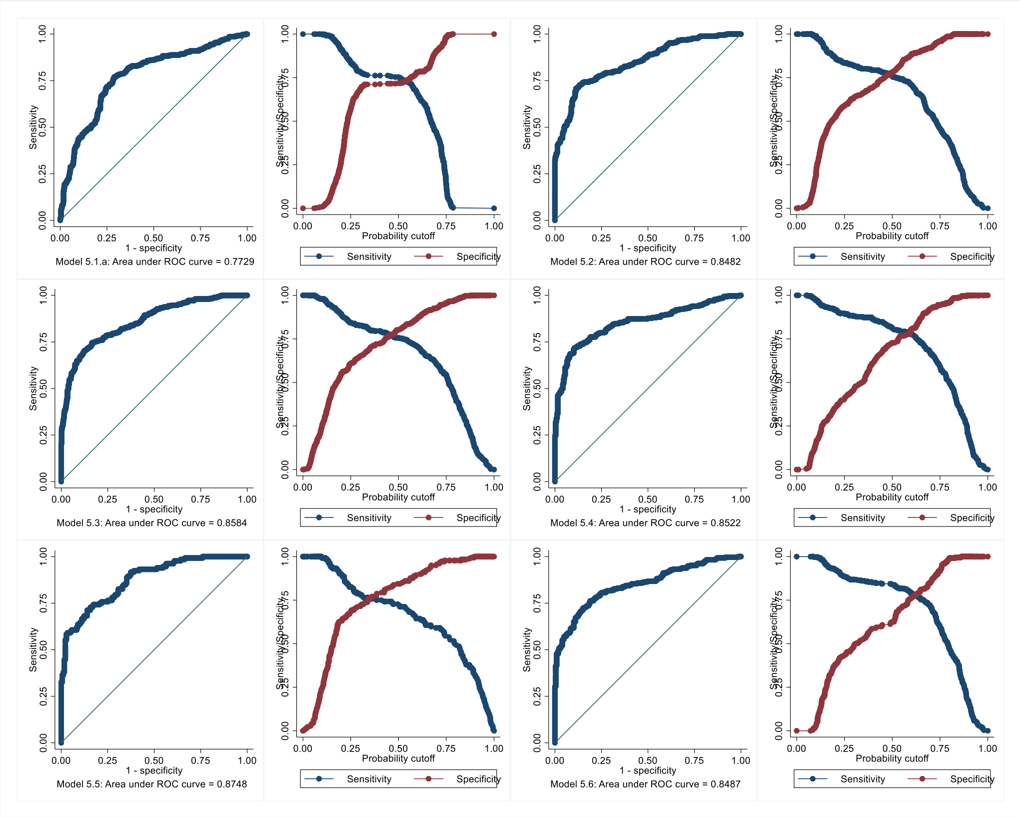
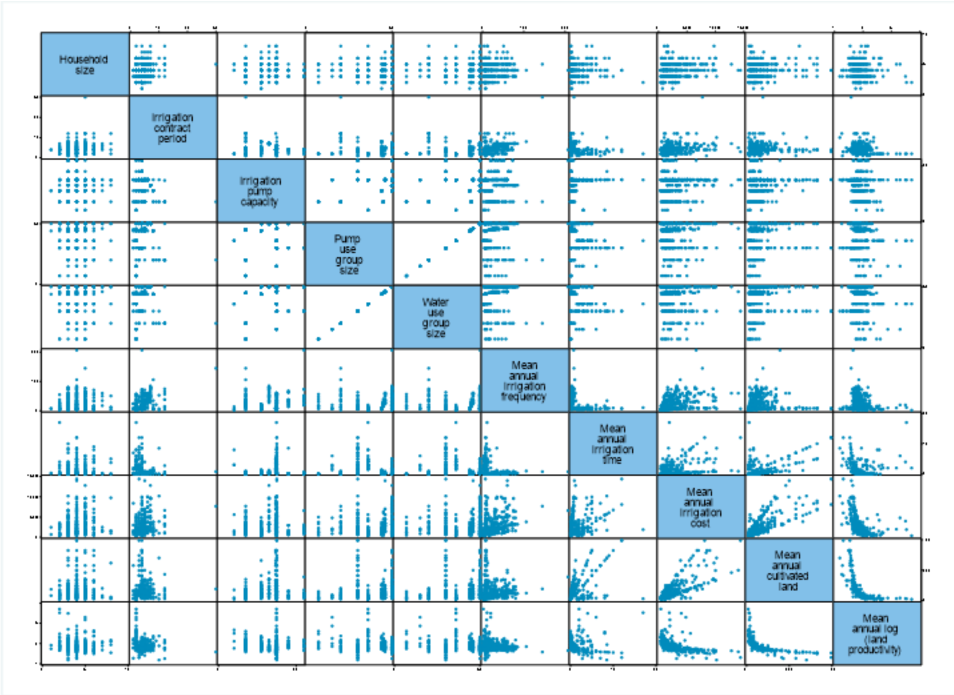
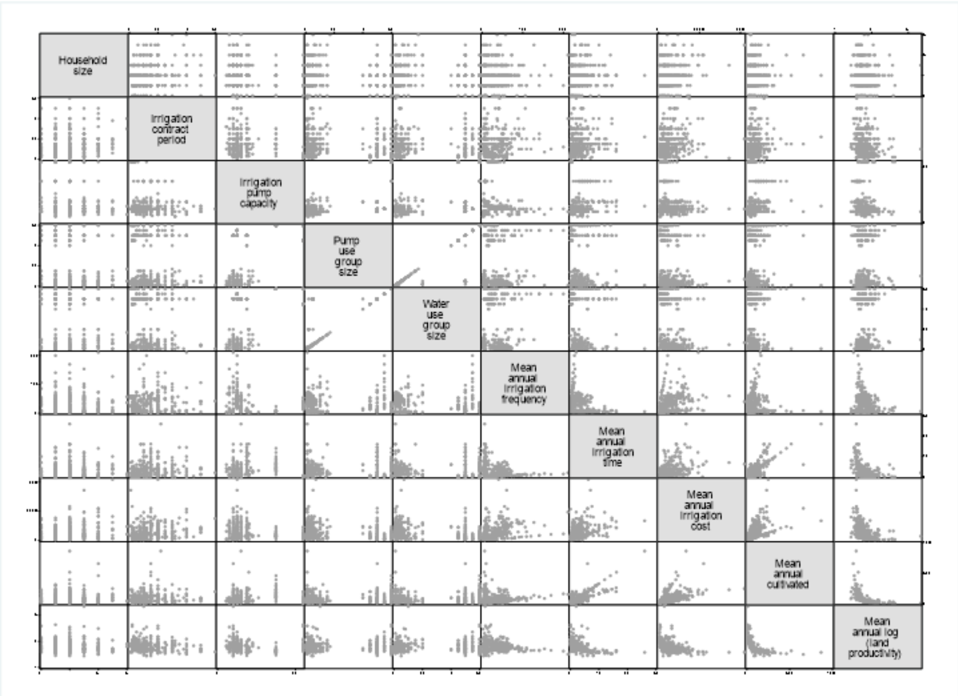


Figure C. 1 ROC analyses of logit regression models for the probability of crop contract choice.
Source: Author's preparation.
Note: This figure depicts the post-estimation ROC analyses of the logit models, Model 5.1.a, Model 5.2, Model 5.3, Model 5.4, Model 5.5 and Model 5.6. Model 5.5 is the most credible in estimating the probability of choosing a crop contract.



(C.2.a)



(C.2.b)

Figure C. 2 Graph matrix of the associations between the selected scale variables.
Source: Author's preparation.
Note: This figure depicts scatter plots of pairwise associations between scale variables. Panel C.2.a shows the scatter plots for solar user and panel C.2.b shows the scatter plots for non-solar users.

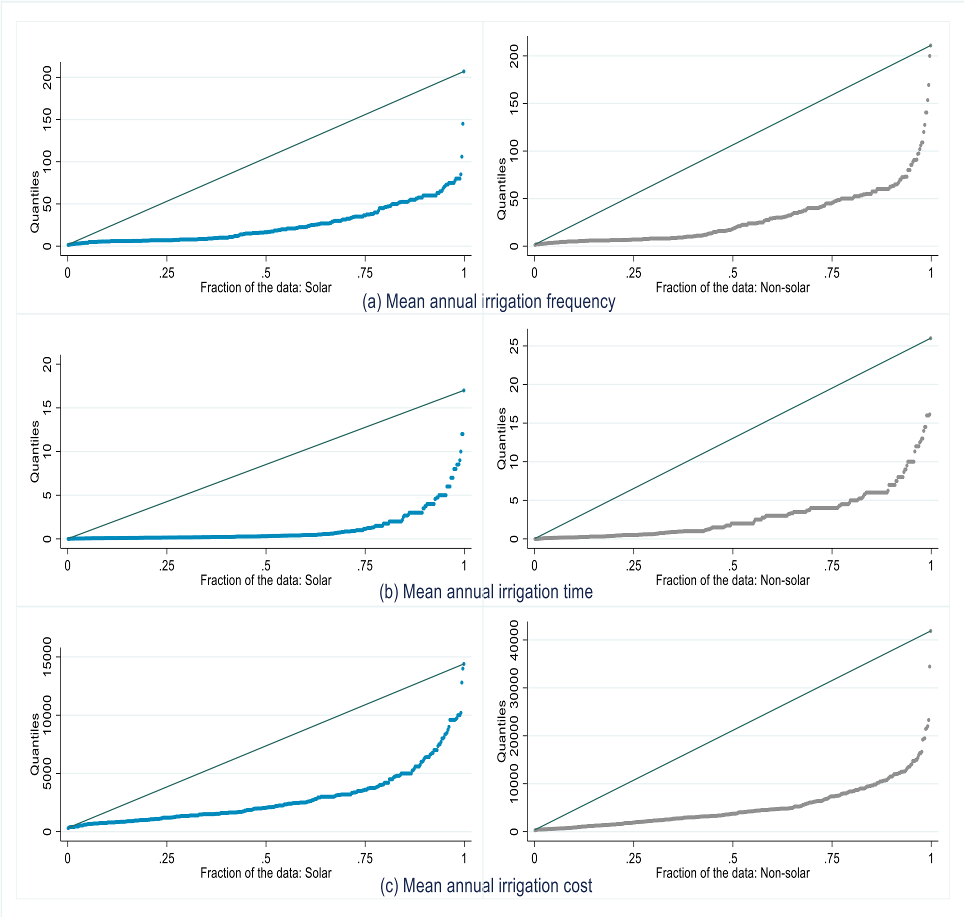


Figure C. 3 Quantiles distributions of irrigation efficiency indicators of solar and non-solar users.
Source: Author's preparation.
Note: This figure depicts the distributions of mean annual irrigation frequency, mean annual irrigation time and mean annual irrigation cost across various fractions of solar and non-solar users.

Table C. 1 Marginal effects of the logit regression models for the probability of choosing a crop contract.

	Model 5.2 Controlled for solar users' institutional accessibility and pump capacity	Model 5.3 Controlled for soil type and land elevations	Model 5.4 Crop contract choice for economic reasons	Model 5.5 Crop contract choice for peer pressure	Model 5.6 Crop contract choice for water management
Variables	Marginal effects	Marginal effects	Marginal effects	Marginal effects	Marginal effects
If use solar irrigation	0.2403*** (0.0755)	0.3189*** (0.0782)	0.2773*** (0.0926)	0.0226 (0.1611)	0.2698*** (0.0971)
If involve in non-farm activity	0.0713 (0.0542)	0.0759 (0.0552)	0.0059 (0.0624)	0.1364 (0.0951)	0.0188 (0.0603)
Household size	0.0061 (0.0202)	0.0116 (0.0206)	0.0116 (0.0252)	-0.0354 (0.0357)	0.0044 (0.0248)
If solar receive agricultural credit	-0.0551 (0.0756)	-0.0546 (0.0766)	0.0344 (0.0898)	-0.1539 (0.1331)	0.0043 (0.1018)
If solar receive agricultural information	0.2783*** (0.0571)	0.2446*** (0.0604)	0.2426*** (0.0610)	0.3855*** (0.1077)	0.2085*** (0.0686)
If solar had a different contract before	-0.0779 (0.0628)	-0.1147* (0.0648)	-0.1487** (0.0706)	-0.0716 (0.1133)	-0.0687 (0.0769)
If have urban market access	0.0862* (0.0475)	0.0642 (0.0497)	0.1493*** (0.0566)	0.1106 (0.0822)	0.1389** (0.0570)
Irrigation contract period	0.0103*** (0.0029)	0.0125*** (0.0031)	0.0135*** (0.0045)	0.0113*** (0.0040)	0.0101** (0.0043)
Irrigation pump capacity	0.0510*** (0.0053)	0.0525*** (0.0057)	0.0527*** (0.0067)	0.0778*** (0.0143)	0.0442** (0.0061)
Mean annual cultivated land	-0.0012*** (0.0003)	-0.0009** (0.0004)	-0.0012*** (0.0004)	-0.0025*** (0.0008)	-0.0007 (0.0005)
If have clay-type cultivated land		0.0415 (0.0490)	0.2033*** (0.0526)	-0.0443 (0.0777)	0.1436** (0.0568)
If have low elevation land		0.1451** (0.0563)			
If have medium elevation land		-0.1476** (0.0574)			
If have high elevation land	--	-0.0541 (0.0505)			
Sample size	800	800	566	311	522
Prob> chi2	0.0000	0.0000	0.0000	0.0000	0.0000
Log likelihood ratio	-388.95	-373.81	-277.49	-134.96	-259.75

Source: Author's calculations.
Note: This table reports the predicted probabilities (odds ratios) of crop contract choice heterogeneity. Appendix C shows the marginal effects and ROC for the models. The following Figure 5.1 visualizes the coefficients and margin comparisons of solar use and its interactions produced from these models. Log likelihood ratios and the significance of chi-2 tests suggest good model fits. The standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table C. 2 Mean regression results of irrigation efficiency indicators for crop and water contracts

	Mean annual irrigation frequency		Mean annual irrigation time		Mean annual irrigation cost		Change in the mean annual land productivity	
Variables	Crop contract	Water contract	Crop contract	Water contract	Crop contract	Water contract	Crop contract	Water contract
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
If use solar irrigation	-22.5244***	0.0018	1.1656**	-0.7347*	-152.3551	-1034.8630	0.1244**	0.0396
	(5.7481)	(5.0288)	(0.4637)	(0.4150)	(347.8720)	(834.9207)	(0.0471)	(0.0414)
Household size	-0.3062	1.3207	0.0441	-0.1268	150.6637*	539.4355***	-0.0148	0.0050
	(1.3094)	(0.9520)	(0.1056)	(0.0786)	(79.2426)	(158.0550)	(0.0149)	(0.0082)
If solar receive agriculture information	1.5870	3.2136	-0.1559	0.0269	435.4839*	-334.3492	0.0844*	0.0237
	(3.7096)	(3.9059)	(0.2992)	(0.3223)	(224.5060)	(648.4766)	(0.0433)	(0.0261)
If solar receive agriculture credit	1.5111	0.3759	-0.1040	0.8318**	-562.4750**	511.2912	0.0928	-0.0816**
	(4.5982)	(5.0658)	(0.3709)	(0.4181)	(278.2791)	(841.0567)	(0.0590)	(0.0362)
If solar had a different contract before	25.6059***	-1.7306	-1.8058***	-0.2005	776.5682***	157.1104	-0.1193***	-0.0695*
	(3.6256)	(4.5979)	(0.2925)	(0.3795)	(219.4191)	(763.3680)	(0.0426)	(0.0371)
If have clay-type land	-9.4523***	10.3961***	0.0550	0.1756	397.4533**	1068.3140***	-0.0241	0.0302*
	(3.2428)	(2.2168)	(0.2616)	(0.1830)	(196.2504)	(368.0459)	(0.0311)	(0.0189)
If have low elevation land	5.2785	-9.0259***	-0.5031*	-0.2061	-337.9077	-135.5892	-0.1341***	-0.0021
	(3.7497)	(2.2314)	(0.3025)	(0.1842)	(226.9292)	(370.4729)	(0.0455)	(0.0181)
If have urban market access	15.2571***	-10.9737***	-1.1081***	-0.2301	-439.0673**	-286.7910	-.0404	-0.0175
	(3.2062)	(2.3683)	(0.2586)	(0.1955)	(194.0406)	(393.2075)	(0.0290)	(0.0176)
Irrigation contract period	0.2233	0.5145***	0.0696***	0.0157	44.0484**	58.9572***	-0.0057***	-0.0004
	(0.2809)	(0.1187)	(0.0227)	(0.0098)	(16.9996)	(19.7152)	(0.0019)	(0.0007)
Irrigation pump capacity	0.4353	-1.4256***	-0.0716**	-0.0316	12.2577	-256.1885***	-0.0004	-0.0111***
	(0.3718)	(0.2732)	(0.0300)	(0.0225)	(22.4995)	(45.3577)	(0.0027)	(0.0027)
If use groundwater	13.2442***	20.9262***	1.4762***	-0.2764	2191.9180***	1987.95***	0.2502***	0.0367
	(4.3337)	(2.7195)	(0.3496)	(0.2244)	(262.2730)	(451.5029)	(0.0348)	(0.0283)
Mean annual cultivated land	0.0568	0.0337	0.0141***	0.0241***	36.1451***	41.1761***		
	(0.0392)	(0.0240)	(0.0032)	(0.0020)	(2.3739)	(3.9789)		
Mean annual yield	0.0009	-0.0019***	0.0004***	0.0001**	0.2768***	-0.4918***		
	(0.0014)	(0.0006)	(0.0001)	(0.0001)	(0.0853)	(0.1062)		
Relative mean annual irrigation cost							-0.1648***	-0.1354***
							(0.0167)	(0.0107)
Sample size	357	443	357	443	357	443	357	443
F-stat	11.25***	15.83***	26.42***	68.37***	75.06***	25.48***	20.64***	25.57***
VIF	1.90	2.17	1.90	2.17	1.90	2.17	1.69	1.79

Source: Author's calculations.

Note: This table reports the detailed mean regression results of mean annual irrigation frequency, mean annual irrigation time, mean annual irrigation cost and mean annual change in land productivity for crop contract and water contract users separately. The standard errors are in parentheses and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Chapter 6

Summary of findings, implications and further research details

This thesis evaluates the factors that can drive the diffusion of climate-smart technology. The three main essays of this research highlight three key features of human capital required for technology uptake and its upscaling. Developing two choice experiments and following a natural experiment approach, it evaluates the correlation between solar irrigation technology use and farmers' i) financial understanding, ii) pro-environmental behaviour, and iii) cooperation level. To conduct choice experiments and a face-to-face field survey, 800 farmers in Bangladesh were recruited. Among 800 farmers, 400 use solar irrigation, and 400 use non-solar (diesel and electricity) irrigation.

This research finds that solar irrigation users have a better financial understanding, they are pro-environmental and their cooperation level is higher than that of non-solar users. Any previous investment experience (agricultural and non-agricultural) increases farmers' risk-taking behaviour. Pro-environmental behaviour is mainly manifested by off-farm and on-farm actions instead of mere perceptions. In the case of perceptions, pro-environmental behaviour depends on how farmers perceive solar and fossil energy and why farmers use solar irrigation. Energy use does not affect the consistency of motivations. Crop contract arrangement, irrigation group size, irrigation length, and economic efficiency improve cooperation among solar users. Farmers living in high solar network areas perform better than those who live in low network areas. Significant household and farm characteristics influencing farmers' dispositions include- farmers' age, education, and farming experience, house condition, assets and farm machines in possession, irrigation pump capacity and contract period, soil quality, land elevations, accessibility of agricultural information, credit, and urban markets, the experience of partial and full crop loss, off-farm and on-farm residue management and farmers' preference and perceptions of energy and sustainable activities. Some specific points of policy suggestions (could be effective in the short- and long-term depending on solar adoption progress in the area) are-

- Use cognitive financial understanding, pro-environmental behaviour, and cooperation intention in the targeting process of potential adopters;
- Use actual adopters' dispositions to promote sustainable use further;
- Incorporate and promote off-farm sustainable practices and diversify on-farm sustainable activities;
- Increase institutional monitoring for technology management and access to markets;
- Send out joint/mutual loans to a group of users to improve the integrity and liability of its use;
- Install green technology to be used with a larger efficiency in terms of the user number and operating length;
- Give flexible payment conditions of technology use and clear notifications/knowledge of community/individual ownership status; and
- Introduce progressive charges in the long-term use of CSA technology to control natural resource extraction.

There are a few important caveats in this research. Firstly, solar irrigation is a given intervention, and farmers' selection for using solar may not be random. Experimental methods could produce biased estimations of outcome variables. To respond to this issue, the sample selection process used similar land distributions of solar and non-solar users, and users in each group are separately and randomly selected. Besides, the regression processes included sets of explanatory variables that are balanced and various robustness (e.g., re-estimation in different models, various measurements of outcome variables, and instrumented solar use) and heterogeneity (e.g., various cohorts of farmers, solar adoption intensity) tests. Secondly, the experimental validity left some concerns. The validity arguments of choice experiments addressed explanatory powers and designs' neutrality. This research did not consider solar adoption drop-outs among non-solar users. Solar user group could be contaminated by the fact that solar energy may or may not cover all of their lands. However, this issue is removed by using input profiles of the 2021-2022 crop calendar separated by energy use only, i.e., cultivation using only solar energy for this group. In designing the choices, questions challenge cognitive thoughts by using competitive frames and choices. There is a possibility of making inconsistent decisions depending on attention and timing. These issues leave the possibility of further inquiries as follows.

Future experimental approaches can use farmers' dispositions focused on this research as intervention trials, treatment trials with a placebo, and the analysis of various cohorts. These methods may elicit impacts- i) before and after technology use, ii) with and without interventions (i.e., monetary and non-monetary nudges), and iii) inclusively and exclusively of all users' dispositions. For example, farmers with larger mobility and living in better provisions could show different cognitive thoughts. Thus, location effect would be a useful focus of analysis, e.g., effects of public infrastructures and utilities, mobility types and frequency, and cultivation difficulties due to weather and climate variables. Solar irrigation pumps do not operate on cloudy days and non-irrigation days. Sample participants in this research are not landless farmers who are primarily local vendors, and vehicle pullers and secondarily casual farm labourers. These locals can receive indirect benefits of a solar pump. Pumps are useful for off-farm purposes and other rural activities, e.g., lighting for local shops, markets, and streets and charging motor vehicles. Landless peers (i.e., casual labourers or other non-agricultural acquaintances) may not have directly given landowners technology choices. However, they can suggest landowners or share information on the utility of a climate-smart technology. Future studies can include farm labourers in the sample and evaluate the dispositions of crop-growers if there is such behavioural spillover.

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Appendix D
Purpose and details of the use of statistical tools and diagnostic plots

Mean

This research uses the statistical tool, mean of a scale/continuous variable to show the representative typical value for the full sample and solar and non-solar users. The mean of a variable is the ratio of the sum of all data points and the number of data points, i.e., observations. The mathematical formula for a variable, with x data points for n number of observations, is as follows:

$$\bar{x} = \frac{\sum x_i}{n}$$

Standard deviation

Standard deviation tool accounts for the variation in the data points of a scale/continuous variable. Thus, it measures the spread of data points relative to the mean value. Mathematically the formula is expressed as the average squared distance between each data point, i and the mean of the data and is written as follows:

$$s = \frac{\sum(x_i - \bar{x})^2}{n - 1}$$

Relative frequency (percentage)

The relative frequency of a given category of a discrete/categorical/ordinal variable is the frequency (number of observations in that category) relative to the total frequency. This is a proportion, calculated often as a percent of a category. For example, f category of a variable has m observations among a total of n observations, i.e., the sample size. Mathematically the formula for the relative frequency of f category is as follows:

$$f = \frac{m}{n} \times 100$$

Skewness and kurtosis

The purpose of calculating skewness and kurtosis in this study is to detect the data distribution of continuous/scale outcome variables for cooperation behaviour. Skewness indicates a lack of symmetry and kurtosis measures the flatness of the distribution of data points. In a skewed distribution, three measures of dispersion, i.e., mean, median and mode do not coincide. The mathematical formula for the skewness of a random variable, X is as follows:

$$\tilde{\mu}_3 = E\left[\left(\frac{X-\mu}{\sigma}\right)\right]^3$$

Here, μ is the mean and σ is the standard deviation. There can be larger data points on either the right side (positively skewed) or left side (negatively skewed) of the density curve of a continuous variable. The mathematical formula for kurtosis is as follows:

$$\tilde{\mu}_4 = E\left[\left(\frac{X-\mu}{\sigma}\right)\right]^4$$

If a density curve has a higher peak than a normal curve, it has a positive kurtosis, and the curve is called leptokurtic and if a density curve is flatter than a normal curve, it has a negative kurtosis and that type is called a platykurtic curve.

Quantiles and percentiles

This study uses quantiles and percentiles to divide the observations into equal groups and observe group differences for the selected outcome variables.

Kernel density plots

Kernel density plots in this research are used to depict the density distributions of a scale variable to find the validity of using a parametric model. This research uses these plots to compare the predicted probabilities of outcome variables for solar and non-solar users and to show the relative volatility between the estimated models. Kernel density is a non-parametric approach to estimate the probability density function of a random (scale) variable based on kernels, or non-negative functions. The function that determines these weights is called the kernel. The density plot (kernel shapes) depicts the distributions of data points over a continuous interval. The peak of a density plot represents the concentration of data points and a longer tail (either right or left) indicates if the data distribution is skewed. The benefit of using kernel density estimation is that it modifies the density curves and shows the estimation variations. The bandwidth of a kernel, in this case, decides on the kernel functions and accordingly the density curves. The summated weighted values, w_i calculated with the kernel function K produce a kernel density estimate and mathematically the formula is as follows:

$$\hat{f}_K = \frac{1}{qh} \sum_{i=1}^{n} w_i K \left(\frac{x - X_i}{h} \right)$$

Here, the selection of the bandwidth, h depends on the values included in the density estimation at each point (Kerm, 2012).

Sample *t*-test

This research uses a two-sample t-test to perform sample balancing tests by comparing means of solar and non-solar users. The null hypothesis in this test is that means of the two groups are equal. A significant t-test implies that I can reject this hypothesis, i.e., means of two groups are statistically significant. Mathematically, the test for two sample means, $\mu_x = \mu_y$ for unknown standard deviations, σ_x and σ_y is as follows:

$$t = \frac{\bar{x} - \bar{y} - \Delta}{\sqrt{\sigma_p^2 \left(\frac{1}{n_x} + \frac{1}{n_y}\right)}}$$

Here, Δ is the hypothetical difference between population means, σ_p^2 is the pooled variance, and n_x and n_y are the two sample sizes. The t-test is also used in this study to confirm the significant effect of a predictor on outcome variables. In this case, the condition in a regression model is that the error term has a normal distribution and the mathematical formula is as follows,

Chi-square test

The chi-square χ^2 test in this research tests the relationship between two categorical variables in logit regression models. A significant chi-square statistic confirms that the relationship is statistically significant. The mathematical formula for this test statistic is as follows:

$$\chi_i^2 = \sum_i^n \frac{(O_i - E_i)^2}{E_i}$$

Here, O denotes the observed value and E denotes the expected value with $k - p - 1$ degrees of freedom. p is the number of parameters and k is the number of categories of a categorical variable.

F-test

The F-test is used in this research as a mean regression model's goodness of fit measure or the overall significance of a regression. The null hypothesis is that all slope parameters included in a model are simultaneously equal to zero, i.e., explanatory variables do not have any effect on the dependent variable. A significant test statistic (p-value is below 0.10 at least) implies that I can reject the null hypothesis. The mathematical measure of the statistic is as follows:

$$F = \frac{ESS/df}{RSS/df} = \frac{ESS/(k-1)}{RSS/(n-k)} = \frac{\hat{\beta}_2^2 \sum x_i^2}{\hat{\sigma}^2}$$

Here, k is the number of variables in a regression model, σ is the standard deviation and β_2 is the parameter. ESS is the explained sum of squares (due to regression) and RSS is the residual sum of squares (due to residuals).

Variance Inflation Factor

The variance inflation factor (VIF) is a post-estimation tool in the mean regression analysis and is used to test multicollinearity among the independent variables included in an OLS model in this research. The multicollinearity test is required to confirm if the included independent variables have statistically significant power to explain the outcome or dependent variable. The mathematical formula is as follows:

$$VIF_i = \frac{1}{1 - R_i^2}$$

Here, R_i^2 is the coefficient of determination, i.e., the sample's representative power of the population. A VIF value is interpreted as the standard error for the coefficient of that independent variable is (that value) times bigger than if that independent variable did not correlate with other independent variables. The rule of thumb is that the VIF of a variable should stay below 10 to avoid high collinearity between independent variables (Gujarati, 2009).

Log likelihood ratio

The value of log likelihood ratio and its significance test are used as goodness of fit measures of probability regression models in this research. The higher the value, the better is the model. Likelihood ratio (LR) follows a χ^2 distribution and a significant p-value indicates that i.e., all independent variable included in a probability model jointly can explain an outcome variable. The likelihood ratio is expressed as follows:

$$LR = -2ln\left(\frac{L(M_0)}{L(M_f)}\right)$$

Here, M_0 is the 0 iteration model and M_f is the final iteration model.

Pseudo-R^2

The pseudo-R^2 is used in this research to observe the goodness of fit of a quantile regression model, i.e., the group size irrigation model for different quantiles. The formula for the statistic is as follows:

$$pseudo\ R^2 = 1 - \frac{sum\ of\ weighted\ deiviations\ about\ estimated\ quantile}{sum\ of\ weighted\ deviations\ about\ raw\ quantile}$$

The higher the value, the model is a better fit for an estimate quantile.

ROC analysis

This research uses ROC analysis to analyse the prediction power of all logit regression models. Logit regression models use ROC analysis to look at the sensitivity and specificity relationships. ROC curves determine the best cutoff value to predict whether a new observation takes value 1 (success), or 0 (failure) otherwise (Hosmer et al., 2013). ROC curve is the location of points plotted as the sensitivity on the Y axis, and 1 – specificity on the X axis. Sensitivity is the fraction of the outcome variable's exactly categorized success observations and specificity is the same as the outcome variable's failure observations. The prediction power of ROC is determined by the area under the curve ranging between 0.5-1. A value greater than 0.5 indicates a better prediction. The graph of sensitivity and specificity as a function of the cut-off probability and the area under the curves implies the predictive power of a model.

Hausman test for IIA (Independence of Irrelevant Alternatives)

This research performs this test to confirm the underlying condition of a multinomial logit regression model for categorical outcome variables. Both Hausman-McFadden (1984) and Small-Hsiao (1985) tests are commonly used to check if categories of a categorical variable are mutually exclusive (Cheng and Long, 2007). Observations are estimated for all categories but one category (this category observations are removed) and then the tests compare these estimates. Let there be m categories of a categorical variable. The null hypothesis in the Hausman test is that the odds of one category (e.g., outcome m vs outcome m-1) are independent of other alternatives. If $chi^2<0$, the estimated model does not meet the asymptotic assumption, and the IIA assumption is violated (Freese and Long, 2000). However, the IIA assumption is based on the condition of the multinomial logit regression model that residuals are not correlated in each equation. This IIA test can be conducted for any base category selection.

Graphs and plots

This research uses various diagnostic plots to show the differences in outcome variables between solar and non-solar users and regression model fits. I use i) line and bar graphs to analyse the scenarios of crop agriculture and energy use in Bangladesh, ii) photographs to explain a solar irrigation system in Bangladesh, iii) bar graphs to compare means of the full sample, solar and non-solar users and mean of odds of choices for solar and non-solar users, iv) matrix graphs for the selected scale variables for solar and non-solar users to find potential associations between explanatory variables and outcome variables, v) quantile plots to observe group differences between quantiles, vi) kernel density plots to show scale variables' density distributions and predicted outcome variables for various categories, vii) heat plot for correlations tables, viii) margins' plots to depict the margin difference for categorical outcome variables, ix) box plots for the fitted values of scale outcome variables, x) ROC plots for logit post-estimations, and xi) coefficient plots for model comparisons.

Appendix E
Survey questionnaire and choice experiments

ID				

Curtin University

Three Essays on the Diffusion of Climate-smart Technology in Agriculture

The Survey Questionnaire
(For Farm Households)

Participant's consent:

☐	I have received information regarding this research and had an opportunity to ask questions. I believe I understand the purpose, extent and possible risks of my involvement in this project and I voluntarily consent to take part in face-to-face survey and experiments.	
☐ I do	☐ I do not	consent to the storage and use of my information in future ethically-approved research projects related to this project
☐ I do	☐ I do not	consent to be contacted about future research projects that are related to this project

Module A. Socio-economic Information

1. Personal identification of the respondent[20]/household:

Name			
Village		Location of the house :	
Union		Latitude	
Sub-district		Longitude	
District			
Agricultural block			
Agro-ecological zone			
Mobile No. (for further inquiry if required):			

2. Demographic information of household members:

Member (No.)	Relationship with the respondent	Age[21] (in years)	Gender [1] Male [0] Female	Education (in years)	Earning status [1] Yes [0] No	Livelihood activity		Income (daily/ weekly/ monthly)
						Main	Secondary	

[20] Respondent in this study is a household member who is responsible for farming management and the relevant record-keeping. Generally in a farming household, the head performs such activities.
[21] Household members below 18 years are also included to calculate the dependency ratio.

Total number of members:								

3. Do you own your house? [1] Yes   [0] No

4. Do you inherit the house[22]? [1] Yes   [0] No

5. How many rooms do you have in your house?

6. What is your house made of? [1] Brick/Cement [2] Tin/Timber [3]Mud/*Kancha* brick [4]Hay/Bamboo/Leaves [5] Other materials

7. What kind of toilet do you use? [1] Sanitary/Slab [2] *Kancha* [3] Open space

8. Does your household have access to electricity?   [1] Yes   [0] No

9. If yes to Q8, how long have you got this access? (year/number of years)

10. Your farming experience (in years):

11. Household asset ownership:

Asset type	Number	Asset type	Number
Mobile		Furniture	
TV		Any electronic device	
Fridge		Any farm machinery (specify)	
Computer		Any farm machinery (specify)	
Internet		Others (specify)	

Module B. Farm characteristics

12. Farm size:

Type of land	Size/ amount (in decimal/ *kantha*/ *bigha*/ *gonda*)
Own cultivable land	
Rented/leased-in land	
Rented/leased-out land	
Homestead land	
Total	

[22] Questions 4-7 are asked to analyse living standard. Living standards will be controlled for in model estimating farmers' pro-environmental behaviour. Farmers' pro-environmental behaviour may depend on their living condition.

13. Do you own any livestock or poultry birds?

[1] Yes [0] No. If yes please specify the number:

Livestock type	Number	Livestock type	Number
Bullock		Chicken	
Cow		Duck	
Buffalo		Pigeon	
Goat		Any other	
Sheep			

14. Land elevation:

Type of elevation	Size/ amount (in decimal/*kantha*/ *bigha*/*gonda*)
Low land	
Medium land	
High land	

15. Soil type:

Soil type	Size/ amount (in decimal/*kantha*/*bigha*/*gonda*)
Clay	
Clay-loamy	
Loamy	
Sandy	
Sandy-loam	

16. What do you think about the fertility of your cultivable land over time?

[1] Increasing [2] decreasing [3] Unchanged or remained the same

If increasing, why (multiple answers are accepted)?

[1] Use of low-carbon inputs during cultivation (e.g., green manure, organic fertilizer, etc)

[2] Changing the type of crop from one season to another

[3] Use of any renewable (i.e., solar) irrigation

[4] Use of any efficient irrigation/tillage method

[5] Others (please specify)……………………………….

If decreasing, why (multiple answers are accepted)?

[1] Every year same type of crop cultivation

[2] Single cultivation in multiple seasons

[3] Use of machinery (e.g., tractor, thresher, harvester)

[4] Use of diesel irrigation

[5] Excessive use of chemical fertilizer

[6] Over-extraction of groundwater

[7] Others (please specify)……………………………….

If unchanged/remained the same, why (multiple answers are accepted)?

[1] Used organic soil correction measures after harvesting (e.g., decomposed organic matter)

[2] Allowed natural predatory species to manage insects

[3] Cultivated soil nutrient-restoring crops periodically (e.g., green manure crops, root crops)

[4] Left fallow on a rotational basis

[5] Others (specify):

17. Do you use any sustainable agricultural method (multiple answers are accepted)?

[1] Efficient irrigation (AWD, drip irrigation, sprinkle irrigation, and so on)

[2] Organic fertilizer

[3] Solar energy

[4] Any traditional/indigenous/local technique (tree stick, birds, lime, ash, and so on)

[5] No-tillage/limited tillage

[6] Others (specify)

[7] Do not use any sustainable agricultural method

18. What are your major irrigated crops (multiple answers are accepted and tick the boxes)?

Crops	Summer	Monsoon	Winter
Rice			
Wheat			
Jute			

Vegetables			
Others (specify)			

19. What do you mostly grow? [1] food crop [2] cash crop [3] fuel crop

20. What cropping pattern do you follow? [1] mono [2] mixed [3] inter [4] multi

21. Crop input-output profile:

Items	Aus	Aman	Boro	Wheat	Vegetables	Jute	Others (specify)
i. Amount of land cultivated (decimal/gonad/kantha/bigha)							
ii. Amount of seed (kg/bigha)							
iii. Cost of seed (BDT/kg.)							
iv. Seedbed preparation cost (BDT.)							
v. Land preparation (cultivation) cost (BDT.)							
vi. Transplantation cost (BDT.)							
vii. Amount of Urea (kg)							
viii. Cost of Urea (BDT/kg)							
ix. Amount of TSP (Kg)							
x. Cost of TSP (BDT/kg)							
xi. Amount of MP (Kg)							
xii. Cost of MP (BDT/kg)							
xiii. Amount of zinc (Kg)							
xiv. Cost of Zinc (BDT/kg)							
xv. Amount of Gypsum							
xvi. Cost of Gypsum (BDT/kg)							
xvii. Fertilizer application cost (BDT/kg)							
xviii. Amount of organic fertilizer or Cow dung (*Gari*/*Maund*)							
xix. Labor costs for other input transportation and application							
xx. Labor cost for weeding (BDT/person)							
xxi. Number of labor during irrigation							

xxii. Labor cost during irrigation (BDT/person)							
xxiii. Cost for herbicide (BDT/kg)							
xxiv. Number of irrigation							
xxv. Average irrigation no. for last 5 years							
xxvi. Electricity/energy required for irrigation (in hours)							
xxvii. Irrigation cost (BDT/hour)							
xxviii. Amount of crops produced (Kg)							
xxix. Harvesting costs (BDT/kg)							
xxx. Crop carrying cost (BDT/kg)							
xxxi. Threshing costs (BDT/kg							
xxxii. Price of crops (BDT/kg)							

Module C. Institutional Accessibility

22. Do you have access to agricultural extension services? [1] Yes [0] No

23. If yes to Q22, where did you get the information and knowledge about crop production, inputs, energy use, and technology?

Name of Sources	Tick (multiple answers are accepted)	Used the source in my cultivation
Neighbouring farmers		[1] Yes [0] No
Agriculture extension service		[1] Yes [0] No
Relatives		[1] Yes [0] No
Research institutions		[1] Yes [0] No
NGOs		[1] Yes [0] No
Mass media (Radio, TV, Newspapers)		[1] Yes [0] No
Others (specify)		[1] Yes [0] No

24. Did you receive any training on any sustainable agricultural method (e.g., i. low-carbon input-use, namely organic fertilizer/green manure, solar energy/irrigation, ii.

efficient irrigation management, namely AWD, drip irrigation, sprinkle irrigation, and so on)? [1] Yes [0] No

25. Do you know when solar irrigation started in your village? [1] Yes [0] No
26. If yes to Q25, in which year did it start in your village? (the year)
27. Do you have a bank account? [1] Yes [0] No
28. Do you or your family members have access to credit? [1] Yes [0] No
29. If yes to Q28, it is from (multiple answers are accepted):

    [1] Bank [2] NGO [3] Others (specify)
30. Do you receive any agricultural subsidy (input subsidy/cash subsidy/agriculture input assistance card) from the government? [1] Yes [0] No
31. Where do you buy and sell your inputs and outputs respectively?

    [1] Local market [2] Urban market [3] At home/village

Module D. Irrigation-energy profile

32. How is irrigation operated on your farm? [1] Power pump [2] Manual
33. If the answer is “Power Pump” for Q32, do you own the pump?

    [1] Yes [0] No
34. If yes to Q33, when did you buy the pump? (which year/how many years back)
35. What was the cost of the pump?
36. How much do you spend on maintenance (annually on average)?
37. If no to Q33, who owns the pump? [1] individual farmer

    [2] the community (cooperative) [3] joint ownership [4] government

    [5] others (specify)
38. What is the capacity of your pump? (in kWh)
39. What is the length of the pump head? (in meters)
40. What is the distance of your land from the irrigation pump? (in km)

41. What is the source of energy used for irrigation on your farm?

[1] Solar [2] Diesel [3] Others (specify)

42. Did you use any other source earlier in the past? [1] Yes [0] No

43. If yes to Q42, what was the source of energy used in the past?

[1] Solar [2] Diesel [3] Others (specify)

44. What is the process of solar transition on the pump you use?

[1] new installation [2] pump conversion

45. If (solar) in Q41, since when/how long have you been using this source?

46. If (solar) in Q41, do you think that irrigation cost has reduced over the years since you switched? [1] Yes [0] No

47. What amount of land can you irrigate? (in decimal/kantha/bigha/gonda)

48. What time of your day do you use irrigation? [1] day [2] night [3] both

49. What is the source of water used for irrigation?

[1] groundwater [2] surface water reservoirs

50. What is the distance of your irrigated land from the water source? (in km)

51. Do you require more fertilizer (any type) during irrigation? [1] Yes [0] No

52. If yes to Q51, how many extra (bags/amount per unit of land) do you need?

Module E: Financial literacy and investment behaviour

53. Have you planned/started any new business/investment/new cropping management in the last 5-10 years? [1] Yes [0] No

(If yes to Q53, go for the following Q54-Q62)

54. What type of investment did you make (multiple answers are accepted)?

[1] New business related to agriculture

[2] New business different from agriculture

[3] New input in cropping

[4] New crop

[5] Others (specify)

55. Do you still make that investment in each production year? [1] Yes [0] No

If no to Q55 ask Q56-Q57,

56. How long did you continue that investment? (in years)

57. Why did you leave the investment?

[1] I did not earn the expected profit

[2] I suffered the loss for consecutive years

[3] I no longer felt required/interested

[4] I Was not able to manage calculations

[5] I was uncertain about income from investment

[6] Others

58. If yes to Q55, how long would you like to continue? (in years)

59. Why would you continue making this investment?

[1] To earn the expected profit

[2] It is required/I am interested

[3] I can manage calculations well

[4] Income is certain

[5] Others

60. After how many years, could you earn the expected profit? (number)

61. Do you make economic calculations before undertaking a new investment?

[1] Yes [0] No

62. If yes to Q61, how do you conduct calculations (multiple answers are accepted)?

[1] Calculate the relative unit costs of the past input and the new input

[2] Compare the profits using the past input and the new input per unit of output

[3] Calculate the costs associated with new input use

[4] Calculate the period of payback

[5] Evaluate the risks of yield loss/low yield using a new input

[6] Others (specify)

Module F: Environmental orientation and perception of energy

63. What is the main extreme climate event in your locality that affected your crops in the last 10 years? [1] drought [2] floods [3] storms [4] thunderstorms [5] cyclones [6] landslides [7] others (specify) [8] None

64. If your crops were affected by any event in Q63, how many times did it happen?

65. What is more valuable to you? [1] Economic benefit [2] Environmental sustainability [3] Both are equally valuable [4] None of the two [5] I do not know

66. Do you think the energy (solar/diesel/others) you use for irrigation is environmentally sustainable? [1] Yes [0] No

67. Why do you use solar while other options are available (only if a solar user) (multiple answers are accepted)?

[1] environmentally safe

[2] less labour cost

[3] application time and system pressure reduces

[4] irrigation cost is low

[5] I did not need to install grids myself

[6] requires less of other inputs (fertilizer, pesticides, and so on)

[7] No harmful impact on human health

[8] crop health is better

[9] Crop quantity increases

[10] others (specify)

68. Do you think that renewable/solar energy should be preferable to fossil?

[1] Yes [0] No

69. If yes to Q68, why do you think so? (multiple answers are accepted)

[1] fossil burning would increase environmental damage

[2] energy is not wasted

[3] if we use energy wisely now, no shortage for the next generations

[4] water is used efficiently

[5] others (specify)

70. How do you manage your crop residue?

[1] Burn on the field

[2] Decompose

[3] Sell them

[4] Do nothing

[5] Fuel use

[6] Animal fodder use

[7] Others (specify)

71. How do you manage your household waste?

[1] Dispose correctly

[2] Throw away randomly

[3] Reuse/recycle/sell if possible

[4] Do nothing

[5] Decompose

[6] Others (specify)

Module G: Technology adoption in collective irrigation

72. Are you a water seller or buyer? [1] seller [2] buyer [3] both seller and buyer

[4] Pump owner/operator [5] Pump owner who sells water

73. How do you pay for your irrigation water supply? [1] hourly rate

[2] for entire season

74. What type of irrigation contract are you in? [1] water contract [2] crop contract

75. How long have you been in this contract? (in years)

76. Number of farmers (including you) using the same, i) pump ii) water source

77. Why did you choose this contract?

[1] irrigation cost is low

[2] energy transition

[3] good terms with water-seller

[4] seller/buyer is a relative/friend

[5] sufficient water supply

[6] Pump nearby

[7] Pump owner/operator

[8] Peer pressure

[9] Others (specify)

78. Did you cancel the contract in the last 5-10 years? [1] Yes [0] No

79. If yes to Q78, why did you cancel it?

[1] Irrigation cost was high

[2] Energy transition

[3] Not on good terms with water seller/buyer

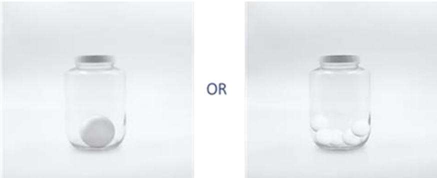
[4] I did not receive/provide sufficient water supply

[5] Payment default

[6] The pump is not in close proximity

[7] Others (specify)

First Choice Experiment

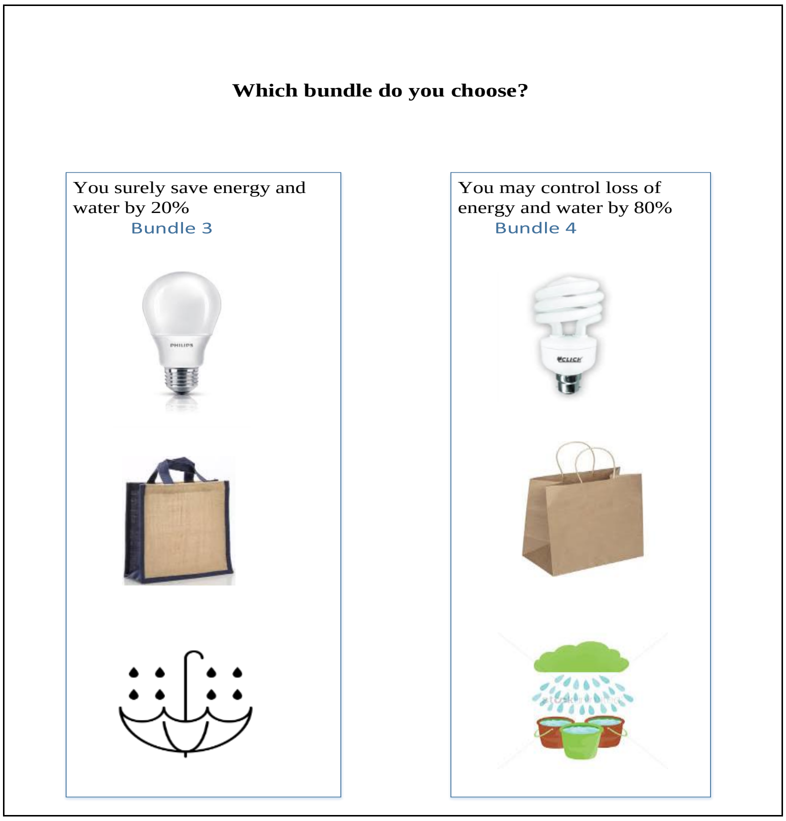
Subjective choice (props)	Objective choice (questions)	Answers
Two boxes are shown to a participant. One box contains one big ball and another box contains multiple small balls.  A. Which box do you choose?	B. Which option will you choose between BDT100 and 1/6th of BDT100 for 7 days? C. What will you choose between BDT100 and 1/6th of BDT100 for the first 3 days and 1/3rd of BDT100 for the remaining 4 days?	
Two boxes are shown to the participant. One is transparent containing one ball and the other is solid containing five small balls. The transparent box contains one ball worth BDT100 and the solid box contains small balls worth BDT20 each. (Participant does not know how many balls there could be in the 2nd box, and the value of the two boxes is the same.)  D. Which box do you choose?	E. (If the participant chooses the 1st box) The value of each ball in the 2nd box increases to BDT25, will you switch to the solid box? (The value of the 1st box remains the same.) F. (If the participant chooses the 2nd box) The value of the 1st box increases to BDT125, will you switch to the transparent box? (The value of the 2nd box remains the same.)	
G. It is possible that one of the boxes containing balls got a hole at the bottom.  Which box do you choose?	I. For which reward will you participate in a lottery game? i. do not want to participate ii. a sure gain of BDT50 iii. 50% chance of winning BDT100 iv. 25% chance of winning BDT150	

H. There is a hole in the box containing small balls, so if you take it you will lose some.  Which box do you choose?	J. For which reward will you participate in a lottery game? i. do not want to participate ii. 50% chance of winning BDT100 iii. 25% chance of winning BDT150 K. For which reward will you participate in a lottery game? i. do not want to participate ii. 75% chance of winning BDT50 iii. 50% chance of winning BDT100

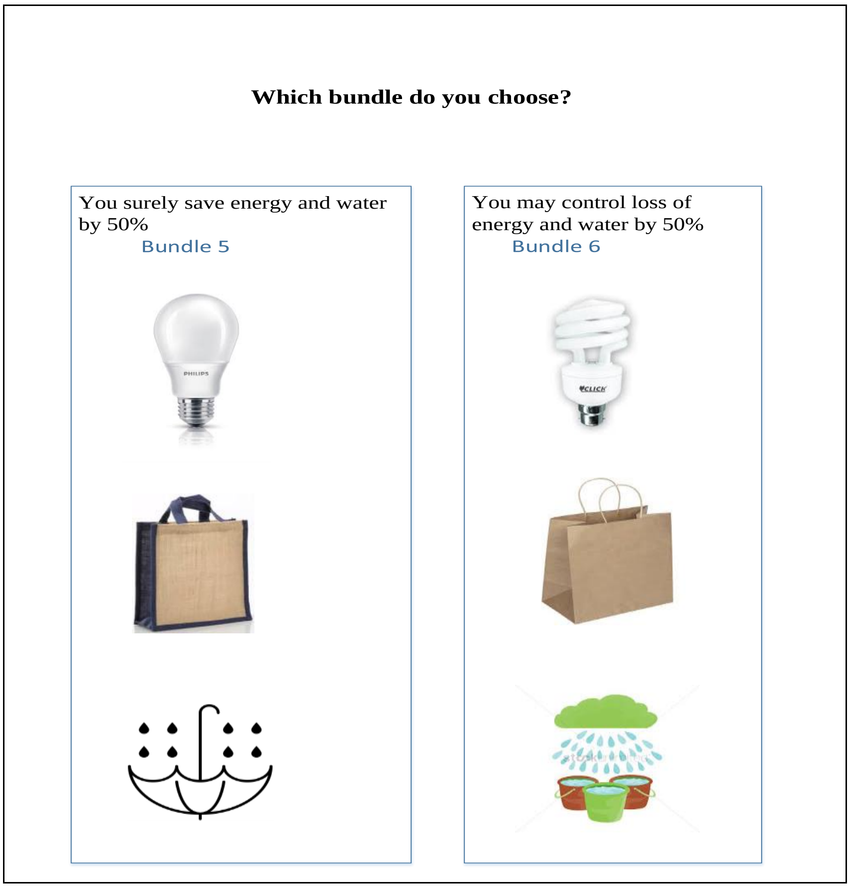
<u>Second Choice Experiment</u>

Frame-set 1: You see two bundles of objects in this image. Bundle 1 contains (from the top) an energy-saving bulb, a jute bag, and an umbrella collecting rainwater. Bundle 2 contains (from the top) a regular bulb, a poly bag, and an umbrella to use when it is pouring. Which bundle do you choose?

Frame-set 2: Bundle 3 contains (from the top) an energy-saving bulb, a jute bag, and an umbrella collecting rainwater with an energy-saving (by 20%) message. Bundle 4 contains (from the top) a different energy-saving bulb, a paper bag, and three buckets storing rainwater in bulk and the message is the possibility to control energy loss by 80%. Which bundle do you choose?



Frame-set 3: Bundle 5 contains (from the top) an energy-saving bulb, a jute bag, and an umbrella collecting rainwater with an energy-saving (by 50%) message. Bundle 6 contains (from the top) a different energy-saving bulb, a paper bag, and three buckets storing rainwater in bulk and the message is the possibility to control energy loss by 50%. Which bundle do you choose?



Thank you for your cooperation!