Evaluating the Impacts of a UNEP Climate Change Adaptation Project by Propensity Score Methods: Evidence from the Central Highlands of Afghanistan

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Abstract

This paper evaluates the impacts of the first climate change adaptation project in Afghanistan, supported under the Least Developed Countries Fund (LDCF). Using a dataset of 235 farmers, we employ two propensity score-based methods—nearest neighbor matching and inverse propensity score weighting—to estimate the community level impacts of the project in Bamiyan and Daikundi provinces. The findings suggest positive impacts of the intervention on female engagement in farming (19-25%), on-farm employment (12-17%), and use of improved types of seeds and crop varieties (11%). Our results, however, do not show any significant project effects on the risk of drought, risk of flood, and farmers' overall vulnerability to climate change. We conclude that while the project has been a successful demonstration of adaptation interventions; in order to fully address the existing and expected climate-related risks (in particular drought), a long-term, full-size intervention should follow.

Keywords: climate change, adaptation, project evaluation, propensity score matching, Least Developed Countries Fund, Afghanistan

JEL: C21, Q25, Q54, Q58

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1. Introduction

In recent decades, climate change has caused impacts on natural and human systems on all contents and across oceans (IPCC, 2014). In a latest survey, Nordhaus and Moffat (2017) estimate the average economic losses of a 3° Celsius global warming at 2% loss of global GDP; a 6° Celsius warming is estimated to cause an 8% loss of GDP. With continuing climate change, adaptation is imperative to maintain and amplify the inherent coping capacity of human and natural systems with adverse circumstances (IPCC, 2014). Adaptation is especially critical for very poor countries (with limited adaptive capacity) like Afghanistan where about 79% of population engaged in agriculture—which is highly sensitive to and potentially affected by climate change and extreme weather events (Baizayee, et al., 2014).

It is certain that adaptation to climate change is complex and involves various geographical, social, economic, and ecological dimensions (Simões, et al., 2010; Dixon, et al., 2014). Consequently, designing and implementing the interventions (in the form of projects, programs, or policies) that meet the needs is challenging.

In order to check whether an intervention has met its targets, impact evaluation is crucial (Gertler, et al., 2016; Khandker, et al., 2010). Evaluating the impacts of a project although can be very costly and laborious, in particular when complex causal links or uncertain framework conditions are involved, providing evidence about the possible effects is indispensable to generating knowledge about what works and what does not (Silvestrini, et al., 2015). Particularly, for the pilot interventions—as they are small scale implementations of potential solutions—rigorous impact evaluation allows the stakeholders to assess the effectiveness of the solutions before expanding the interventions in full. This is specifically of great relevance to Afghanistan as the country has implemented its first pilot climate change adaptation project: *Building Adaptive Capacity and Resilience to Climate Change in Afghanistan*. The project is supported by the Least Developed Counties Fund (LDCF) under the Global Environmental Facility (GEF) (Baizayee, et al., 2014).

In this paper, we provide firsthand evidence on the impact of the LDCF project on the farming communities in the Central Highlands of Afghanistan. Specifically, we estimate the outcomes of the farmers in untreated communities to investigate the average treatment effects of the project on the adaptation behavior of the farmers in the covered communities. To this end, we evaluate the outcomes specified in component 3 of the project (Reducing climate change vulnerability in the selected project sites through local institutional capacity building and concrete interventions to improve water use efficiency) and additionally, three other related outcomes—

gender mainstreaming (by analyzing the number of females engaged in farming activities)[2], *on-farm employment* (by analyzing the total labor engaged in farming)[3], and *farmers' overall vulnerability to climate change*[4].

Estimating the average treatment effects (ATT) requires an estimation of the counterfactual. In observational studies, where the treatment is not assigned randomly, the difference in means is in general a biased estimator of the ATT. Given the non-experiment nature of our data, we use two propensity score-based estimators—nearest neighbor matching (NNM) and inverse propensity score weighting (IPW)—to counter for the selection problem (Dehejia & Wahba, 2002; Stuart, 2010) and estimate the community level ATT of the LDCF project in Bamiyan and Daikundi provinces.

Under both estimators, our findings show significant project impacts on women engagement in farming, on-farm employment, and use of improved seed and crop varieties. No significant project impact, however, was observed on risks of drought and flood and overall farmers' vulnerability to climate change. Considering the severity of existing and expected risks associated to climate change (in particular drought) and the fact that the LDCF project was implemented as a pilot test, it is recommended that a full-size intervention should follow the evaluated project.

The remainder of the paper is organized as follows. An overview of climate change and adaptation in Afghanistan is provided in Section 2. Section 3 overviews the estimation approach. Methods and materials are presented in Section 4. Section 5 describes the results. Discussions are presented in Section 6. Section 7 concludes.

2. Climate Change and Adaptation in Afghanistan

Afghanistan is a mountainous country with generally cold winters and hot summers (Savage, et al., 2009). The country has an extreme continental arid climate that is characterized by desert, steppe, and highland temperature regimes. Strong solar radiation and copious sunshine, low

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2 Females play an essential role in community-based management of natural resources. The project aimed at increasing female engagement in farming activities, in particular bee-keeping, gardening, and harvesting the forest products and fruit (as documented in the fact sheet of the LDCF project for Bamiyan and Daikundi provinces).

3 As a result of climate change and prolonged droughts in recent years, many farmers became unemployed. Adaptation interventions, like LDCF, should restore the on-farming employment of the farming household members by increasing farm productivity and profitability, increase in yield, planting new tree species, and removing various farming constraints.

4 The overall objective of the LDCF project is to increase the adaptive capacity and increasing the resilience of the rural communities to climate change; as a result therefore, decreasing their overall vulnerability to the impacts of climate change (https://postconflict.unep.ch/publications/Afghanistan/LDCF_english.pdf).

relative humidity, and high evaporation are among other characteristics of the country's climate (Shroder, 2014).

The country is divided into five climate regions. The Hindukush Region in the northwest: receives the highest amount of precipitation and is therefore a major source of water; the Northern Plains: mainly covered by grassland and is very important for agriculture; the Central Highlands: characterized by deep valleys and mountain ranges up to 6400 m; the Eastern Slopes: mostly covered by forests; and the Southern Plateau: the largest region and mainly covered by arid desert (Aich & Khoshbeen, 2016).

Analysis of the historical climate data shows a significant change in the climate of the country since the 1950s (Aich & Khoshbeen, 2016). The change has happened in the form of increase in the average temperature (1.8° Celsius), decrease in average precipitation (with variation across time and space[5]), and more frequent extreme weather events, especially drought (WFP; UNEP; NEPA, 2016; Aich & Khoshbeen, 2016).

The evidence shows that not all countries and communities are equally affected by climate change. Developing countries are becoming increasingly vulnerable to the consequences of climate change and extreme weather events, such as drought and flood (Campen & Schellnhuber, 2009; Esham & Garforth, 2013; Altieri & Nicholls, 2017; Shaffril, et al., 2017).

Vulnerability, as defined by Silvestrini, et al. (2015), is a function of exposure and sensitivity to, and the ability of a system to cope with, adverse effects of climate change and extreme weather events. With changing climate; it is obvious that Afghanistan's natural and human systems are exposed to the consequences of these changes (exposure). Moreover, the dependency of majority of population on agriculture and the arid climate make the country very sensitive to the effects of climate change (sensitivity). Furthermore, due to more than three decades of instability (civil war and armed conflict) and extreme poverty, the country's adaptive capacity is very limited at all levels (household, local, and institutional). Overall, these factors together make Afghanistan one of the most vulnerable countries to the impacts of climate change (Baizayee, et al., 2014).

Compared to the degree of vulnerability and magnitude of impacts, current adaptation interventions are very limited. Although a number of projects have been implemented that supported farmers to build and enhance their adaptive capacity[6], only one pilot project

5 Spring precipitation decreased significantly.

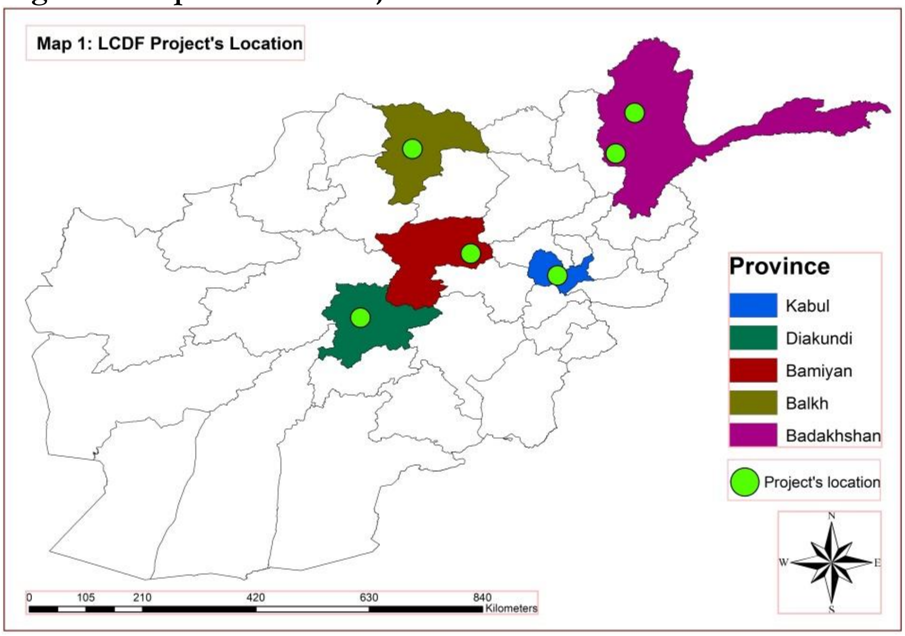
6 Two examples are Action Aid (www.actionaid.org/afghanistan/stories/building-water-storage-tank-ensure-food-security-and-community-health-central-af) and Agha khan Foundation (www.akdn.org/sites/akdn/files/Publications/2010_akf_brief_bamyan.pdf).

exclusively aimed to increase the resilience of the farming communities to climate change: the LDCF project, whose impacts at the community level are estimated in this study.

In late 2012, the government of Afghanistan secured funding for a full-size project—*Building Adaptive Capacity and Resilience to Climate Change in Afghanistan*—under the Global Environmental Facility (GEF)[7]. The project was designed to increase the resilience of vulnerable communities and build capacity of local and national institutions to address climate change risks in Afghanistan through achieving the following four outcomes: (1) increasing the capacity and knowledge base for assessment, monitoring, and forecasting of climate change-induced risks to water sources; (2) mainstreaming climate change adaptation into policies and planning; (3) reducing climate change vulnerability in the selected project sites through local institutional capacity building and concrete interventions to improve water use efficiency; and (4) increase knowledge and awareness of climate change adaptation and best practices at the national, provincial, and community levels (Baizayee, et al., 2014).

At the community level, the project (piloted as small-scale demonstration interventions) has been implemented[8] for four years (May 2013–May 2017) in Badakhshan, Balkh, Bamiyan, and Daikundi provinces (the map is depicted in Figure 1)—aimed to address two major climate change-related risks: drought and flood.

Figure 1. Map of LDCF Project Locations.



7 Afghanistan is a beneficiary of the climate change adaptation project supported by the Least Developed Countries Fund (LDCF) under GEF.

8 The LDCF project has been implemented by the Afghanistan's National Environmental Protection Agency (NEPA) with the technical support of United Nations Environmental Program (UNEP) (Baizayee, et al., 2014).

The targets of the project were specified by conducting a baseline assessment[9]. Table 1 presents the targets that we are addressing in this study; namely the Component 3[10].

Table 1. Relevant official project indicators, baseline, and targets.

Outcome	Indicator	Baseline	Target
3.1.	The number of households with access to efficient water management technologies (including drip irrigation, water storage systems, and water canals) for flood and drought management.	Only surface and canal irrigation systems are used. No affordable micro-irrigation techniques (AMIT) used.	424 households will have access to AMIT; 10,500 m^3 increased water storage capacity in check dams; three new dams will be constructed.
3.2.	Total agriculture area (ha) where agriculture management techniques adapted to intensive and prolonged droughts are practiced. Such activities include use of drought-tolerant crop varieties, diversification of crops, use of climate change adapted cultivation practices, and maintenance of seed bank.	In none of the sites specific agricultural-management techniques adapted to intensive and prolonged droughts.	One dryland research and education station; 200 ha of agricultural land planted with drought-tolerant crops; 200 ha of micro catchment techniques; 100 ha of degraded watershed slopes restored with multi-use tree species and native rangeland species.
3.3.	Flood-mitigating infrastructure implemented in study sites.	None.	120 ha of rural areas newly planted with species that provide ecosystem services such as water catchment, soil stabilization, and flood protection; 140 ha of low-cost water barriers and catchment structures for each of 3 per urban villages in the target province of Daikundi.
3.4.	Survivorship of newly planted trees 24 months after plating data.	Not available.	Minimum 60% of the newly planted trees will survive.

9 See Baizayee, et al., 2014

10 Beyond the community level, the project also aimed to increase the capacity of relevant national organizations to address climate change risks. Here we focus on the direct impact on farmers and communities. The analysis of improved capacities of national organizations is arguably harder to quantify and goes beyond the scope of this paper. Baizayee, et al., 2014 provide a complete list of indicators, baseline values, and targets.

3. Estimation Approach: Propensity Score Matching

This section describes the empirical approach we use for measuring the impacts of intervention on outcomes of interest. For the evaluation of the effect of a policy intervention (i.e. the treatment; $T_i: T_i = 1 \text{ for } treatment; 0\ otherwise$)—in our case T is the LDCF project—on a certain outcome (Y), ideally one would want to compare two potential outcomes for each individual i: first, the outcome with the treatment, $Y_i(1)$; and second, the outcome without the treatment, $Y_i(0)$. Then, the mean causal effect of the treatment (T) on the treated individuals would have been the average treatment effect on the treated (ATT) defined as

$$ATT = E[Y_i(1) - Y_i(0)|T_i = 1] = E[Y_i(1)|T_i = 1] - E[Y_i(0)|T_i = 1] \qquad (1)$$

The fundamental problem, however, is that we cannot observe both $Y_i(1)$ and $Y_i(0)$ at the same time; that is, individual i cannot be, at the same time, treated and not treated (Holland, 1986). To solve the problem, we have to estimate the counterfactual: the outcome of the treated individuals in the absence of treatment.

One way to estimate the counterfactual, and obtaining ATT, is to run a randomized experiment; that is to allocate the individuals in treatment and control groups randomly (Davis & Holt, 1993; Bradsley, et al., 2010; Kagel & Roth, 2015). If randomization is done properly, treated and non-treated individuals would be homogeneous in terms of all characteristics other than Y and T. The key advantage of randomization is that the individuals or agents do not control the treatment assignments, in other words, treatment status is independent of the potential outcomes: $Y_i(\cdot) \perp T$. Randomization, however, may not always be feasible or even ethical (West, et al., 2008; Wooldridge, 2009).

In observational studies for causal effects, treatments are assigned non-randomly.[11] As a result, treatment and non-treatment groups may differ systematically with respect to relevant characteristics, therefore, may not be comparable (Rosenbaum & Rubin, 1983). This problem, however, can be solved if the Conditional Independence Assumption (CIA) holds. CIA states that conditional on some observable confounders X, the treatment variable is independent of potential outcomes:

$$Y_i(\cdot) \perp T|X \qquad (2)$$

[11] In the absence of randomization, either individuals or agents (or both) could control the treatment assignment– which would then lead to the well-known problem of selection bias.

CIA insures that after controlling for X, there is no systematic difference between treatment and control groups. In this sense the role of X is to balance treatment and control individuals such that individuals are sub-grouped (based on X), and then only treated and non-treated individuals who fall in the same sub-group are directly compared. The problem with this method is that as the dimension of X increases the number of sub-groups increases exponentially. This problem can be addressed using a scaler function of X, namely the propensity score, that summarizes the information required to balance the distribution of X (Rosenbaum & Rubin, 1984).

Propensity score is the conditional probability that an individual will receive treatment given X. That is

$$p - score = P[T_i = 1|X] \qquad (3)$$

Rosenbaum and Robin (1984) have shown that CIA still holds true if X is replaced by p-score, as defined in (3). It means that if data justify matching on X then they also justify matching on p-score. The p-score can be estimated using a logit or a probit model.

In addition to CIA, the estimated p-score needs to generate a high level of overlapping between common treated and non-treated individuals. The overlap or common support condition (CSC) requires p-score to be bounded between zero and one.

While CSC can be tested graphically, CIA is not directly testable; however, it has some testable implications. In practice, to make sure that CIA is not violated, the covariates balance is crucial. Covariates balance can be tested using standardized difference of means/standardized bias ($\mathrm{SD/SB}$) and variance ratio (VR) defined as

$$SD = \frac{\bar{X}_T - \bar{X}_C}{\sqrt{\frac{(S_T^2 + S_C^2)}{2}}}, \;\; SB = |SD|.100\%, \;\; VR = \frac{S_T^2}{S_C^2} \qquad (4)$$

where $\bar{X}_T$ and S_T^2 are the mean and variance of covariate X for the treated individuals and $\bar{X}_C$ and S_C^2 are the mean and variance of the covariate X for the non-treated individuals.

Although there is no clear consensus on the threshold values of SD and VR, in practice an $|\mathrm{SD}|$ less than 0.1 (an SB of less than 10%) and a VR between 0.5 and 2 for each covariate indicate satisfactory covariates balance (Austin, 2011). A $|SD|$ greater than 0.2 (an SB of greater than 20%) can signal serious covariate imbalances.

The CIA can still be violated if there are unobserved confounders. In such case a problem of *hidden bias* may arise. To check the robustness of the results against a hidden bias, a sensitivity analysis is recommended by investigating the Rosenbaum bounds (Rosenbaum, 2002). In sensitivity analysis, one determines how strongly an unmeasured variable must influence the selection process in order to undermine the implication of matching analysis (Caliendo & Kopeinig, 2005). It is important to note that Rosenbaum bound is the worst case scenario (DiPrete & Gangl, 2004).

Under satisfactory covariate balance (and hence CIA under observed confounders) and CSC, p-score can be used to generate unbiased estimators of ATT. Popular ways to do so include matching, reweighting, and stratification. Although there is no consensus on the best method, using more than one method is recommend to ensure the robustness of the results (Caliendo & Kopeinig, 2005; Khandker, et al., 2010).

Propensity score-based methods are widely used to evaluate the impact of interventions where control randomized experiment is either not possible or not appropriate (Ali & Erenstein, 2017; Antlea, et al., 2018; Barth, et al., 2006; Becerril & Abdulai, 2010; Cushman & Vita, 2017; Hudson, et al., 2014; Jalan & Ravallion, 2003; Kalaj, 2009; Khonje, et al., 2015; Lebert, 2016).

4. Materials and Methods

This section first describes the study area, which is located in Bamiyan and Daikundi provinces (depicted in Figure 1). We then introduce and define the related variables and provide their descriptive statistics. The sampling method and data are also described. We finally check the CIA and CSC assumptions.

4.1. The Study Area

Our study area consists of 24 Community Development Councils (CDC)[12] in Bamiyan center (center of Bamiyan[13] province) and Nili (center of Daikundi[14] province).[15] The two provinces are of the beneficiaries of the LDCF project. From these 24 CDCs, 12 of them received the project

12 CDC is a democratically elected body in the community level that has been introduced through National Solidarity Program (NSP) of the Ministry of Rural Rehabilitation and Development (MoRRD). One or several villages, depending on their size, can form a CDC.

13 Bamiyan is a mountainous province where the Baba Mountain Range extends from east to the southwest and west of the province, providing the origin for many of the country's rivers, including Kunduz, Helmand, Kabul, and Hari Rood. Steep mountain slopes, deep valleys, and harsh winters characterize the landscape of Bamiyan. The people in Bamiyan rely predominantly on rural agriculture and livestock husbandry for their livelihood.

14 Daikundi is one of the most vulnerable provinces to climate change in the country. The province experiences acute water shortages and droughts and has a poor soil quality. Agriculture is the main source of income for the residence of this province.

15 We need to address the caveat that our resources for traveling and collecting data in Afghanistan were financially constraint. We therefore concentrated our efforts on Bamiyan and Daikundi provinces. To investigate the overall impact of the project, apart from including other components of the project, the impact of the project should be studied in Badakhshan and Balkh provinces as well.

(treated CDCs) and the remaining 12 were not covered (non-treated CDCs). The treated CDCs were selected (by NEPA and UNEP) based on their location in Shah-e-Foladi Protected Area (in Bamiyan center) and in pre-urban areas (in Nili). The non-treated CDCs were selected from the same areas and after a careful evaluation of nearby CDCs. The selection of the non-treated CDCs has been crucial in making sure that the CDCs in both groups had been similar (in observable characteristics) prior to LDCF intervention. This identification process greatly reduced the likelihood of unobserved confounders.

20 of the selected CDCs are located in the Bamiyan center and the remaining 4 are located in Nili. From each 24 CDCs, a specific number of farmers were selected randomly[16] for interview. The interviews were carried out with the heads of the households. In total 235 farmers were interviewed in 12 valleys[17].

4.2. Dataset and Variables

This study uses a primary dataset collected in the study area in the summer of 2017. A multistage sampling method was employed for choosing the subjects and collecting the data. First, the CDCs, which are covered by the LDCF project, were identified; and for each treated CDC, a similar CDC, which is located in the same valley and is not covered, was selected. Then, a specific number of farmers (heads of households) from each CDC were randomly selected for interview. The interviews were based on a detailed structured questionnaire containing 6 sections: (1) Valley and CDC; (2) Personal and Household; (3) Farm and Income; (4) Climate Change Perception; (5) Climate Change Adaptation and LDCF project; (6) Climate Change Risks[18].

Based on our model, the variables are described in three categories: covariates (X), treatment (T), and outcomes (Y). The variables and their descriptive statistics are presented in Table 2. The vector of covariates includes all variables that are associated with treatment assignment and are affecting the outcomes. The vector does not include the variables that are affected by the treatment. The treatment is a dummy variable, T_i, which is 1 if the farmer i is —

[16] In Bamiyan center: In each CDC, the first household to interview was selected randomly from the proximate number of households living there. The remaining households were chosen using systematic random sampling.

In Nili: The household were randomly selected from the list provided by the NEPA-Daikundi and were interviewed in cooperation of the head of the CDCs.

[17] Table A.1 in appendix A presents the CDCs that are covered by the current study, their treatment status, and the distribution of the sample.

[18] Appendix B provides the English translation of the instruments.

Table 2. Definition of variables and descriptive statistics[19].

Category	Variable	Mean	St.Dev
Treatment variables			
	LDCF Project (Dummy)	.485	.50
	Rate the LDCF Project	.95	.22
Dependent variables (outcome) *[Relevance to the project]*			
[Overall project impact]	On-farming employment	3.17	1.66
[3.1. & 3.2. (Table 1)]	Use of improved seeds and crop varieties	.53	.50
[3.1. & 3.2. (Table 1)]	Risk of drought	3.25	1.80
[3.1. & 3.3. & 3.4. (Table 1)]	Risk of flood	2.60	1.25
[Gender mainstreaming]	Number of female working on farm	1.69	1.21
[Overall project impact]	Farm vulnerability to climate change	.58	.49
Independent variables (covariates)			
	Age	40	15.76
	Farming experience	24	15
	Main job	Farming (156); Other jobs (79)	
	Main cause of climate change	God's will (180); others (55)	
	Change in average temperature	.94	.24
	Change in average precipitation	.90	.29
	Farm size	17.14	15
	Valley	Table A.1 (Appendix A)	
	Irrigation water (River)	.52	.50
	Irrigation water (Karez)	.35	.48
	Irrigation water (Stream)	.14	.35
	Small farmland	.57	.50
	Poor soil fertility	.07	.26
	Hours with access to electricity	6.32	3.26
	Car	.2	.43

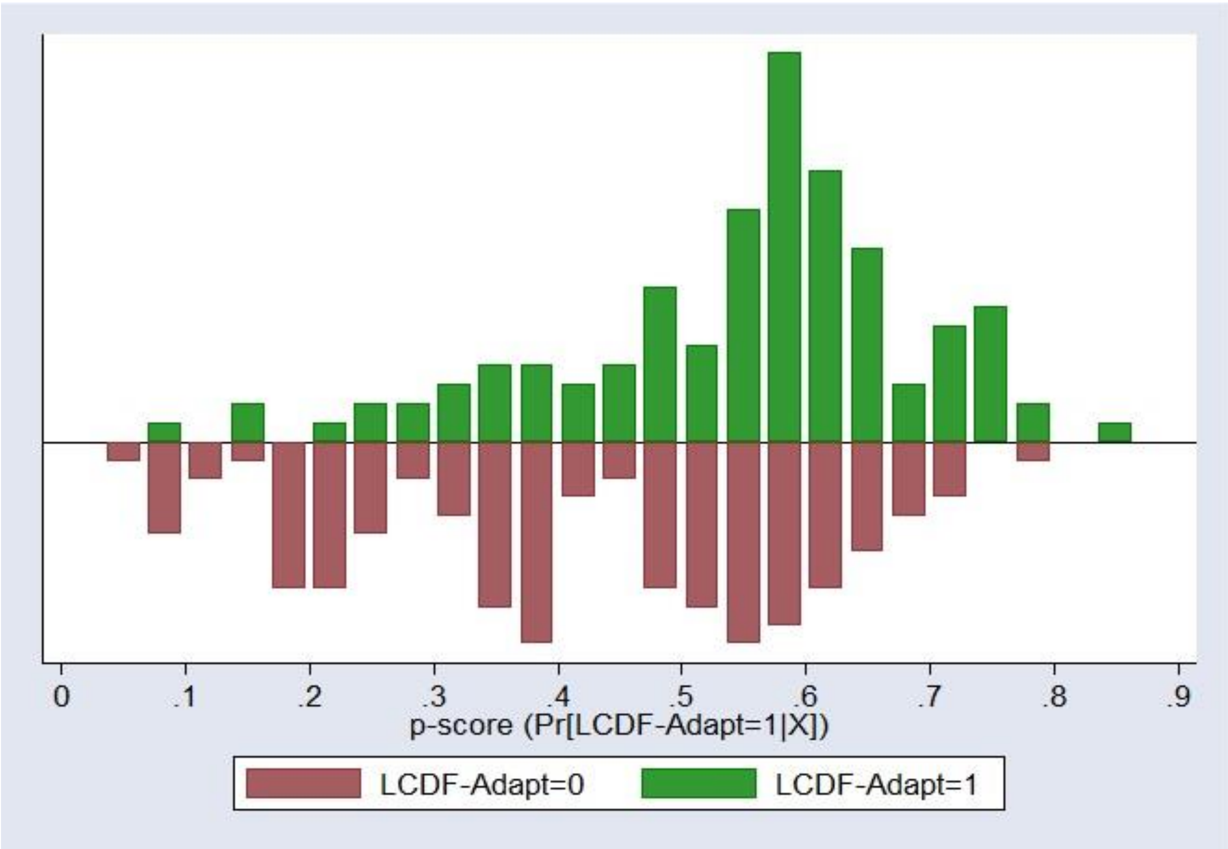
[19] Details of the instruments are provided in Appendix B.

treated and 0 otherwise. In our sample 114 farmers are treated and the remaining 121 farmers are not treated. The vector of outcomes includes six variables that measure the impacts (direct or indirect, intended or not intended, positive or negative) of the intervention.

The CIA and CSC are key assumptions in order to estimate the ATT using a propensity score-based method. The CSC states that the estimated p-scores (for each individual) should be in the $(0,1)$ interval. This can be tested graphically. Figure 2 shows that the estimated p-score (which we estimated using a logit model) satisfies the CSC. Based on Figure 2, all estimated p-scores are in the $(0.06,0.86)$ interval. In fact, the estimated p-scores not only satisfy the CSC, but also provide a very good overlap by putting minimal mass at the tails.

The CIA is not directly testable. It, however, has testable implications. To make sure that the CIA is not violated; the covariates should be balanced in a satisfactory level. Under the estimated p-score, CIA is not violated if, for all covariates, SD is, ideally, less than 0.1[20] (SB is less than 10%)[21] and VR is in the $(.5, 2)$ interval.

Figure 2: Common support condition (overlap).



20 The SD values which greater than 0.2 would be a signal of some serious covariate imbalances.

21 Rubin (2001) provides detailed illustrations on the threshold values of SD/SB.

Table 3. Covariate balance summary (NNM and Weighted).

Covariate	Standardized Bias			Variance Ratio		
	Raw	Matched	Weighted	Raw	Matched	Weighted
Sqrt(HrsEl)*IrWStream	14%	10%	1%	.56	.96	.76
Sqrt(FarmingEx)	22%	2%	6%	1	1.2	1
Sqrt(Age)*Fcsoilfertility	3%	10%	7%	.89	1.4	1.3
Sqrt(FarmSize)*FCSmallFland	3%	.6%	1%	1	1.3	1.1
Sqrt(FarmingEx)*Tem	20%	1%	6%	1	1.1	1
Car	9%	2%	6%	1.1	1.4	1.2
CCC						
2	8%	5%	6%	.85	1.1	.88
3	19%	9.5%	3%	.50	1.6	1.1
MainJob						
1	26%	11%	.2%	.37	1.9	1
2	22%	7%	1%	.71	1.1	1
3	16%	0%	2%	.55	1	.89
Valley						
2	4%	3%	1%	1.1	.91	1
3	7%	0%	.5%	.81	1	1
4	1%	0%	2%	.96	1	1
5	13%	0%	1%	1.6	1	1
6	7%	0%	3%	1.3	1	1
7	2%	6%	2%	1	1.2	.94
8	1%	0%	7%	.96	1	.81
9	1%	6%	.7%	.96	1.2	1
10	5%	3%	.3%	1.2	.88	1
Fcsoilfertility	1%	11%	9%	.94	1.55	1.4
FCSmallFland	2%	8%	1%	1	1	1
IrWRiver	17%	2%	7%	.98	.99	.98
IrWKarez	4%	4%	6%	.56	.96	.96
IrWStream	12%	3%	3%	.78	1	.93
Tem	2%	4%	3%	.93	1.1	1.1
Pre	40%	11%	2%	.27	1.96	1.1

As can be observed in Table 3, both estimators (NNM and IPW) create high degree of covariate balance, particularly by reducing the standardized bias (standardized difference in means). All SD/SB and VR values fall within the ideal range. Hence and if there is no unobserved confounder, the CIA is not violated.

5. Results

The community level impacts of the project at our study sites are investigated by examining associated outcomes using NNM and IPW estimators. The empirical assessment consists of analyzing the related outcomes such as risks of drought and flood; on-farm employment; female engagement in farming; use of improved types of seeds and crop varieties; and overall farmers' vulnerability to climate change.

The results, presented in Table 4, show significant positive project impacts on outcomes like on-farm employment, female engagement in farming, and use of improved types of seeds and crop varieties. Specifically, on-farm employment is 12-17% higher for the households that received the project. In the same way, female engagement in farming activities is significantly higher (19-25%) among treated households. Similarly, under both NNM and IPW, the covered households used more (11%) of improved types of seeds and crop varieties than the farmers in non-treated communities.

The estimated results do not show any significant project impact on risks of drought and flood. Identically, no significant project impact is observed on overall vulnerability of farmers to climate change.

Table 4. Average treatment effects (ATT) of the LDCF project.

Matching algorithm	Outcome	ATT (Std. Err)
Nearest neighbor matching	On-farm employment	.54**
		(.26)
	Women engagement in farming	.42**
		(0.18)
	Use of improved seeds and crop varieties	.11*
		(.06)
	Risk of drought	-.04
		(.20)
	Risk of flood	.28
		(.18)
	Farmer's vulnerability	.008
		(.06)
Inverse propensity score weighting	On-farm employment	.38*
		(.23)
	Women engagement in farming	.32**
		(.16)
	Use of improved seeds and crop varieties	.12*
		(.06)
	Risk of drought	-16
		(0.18)
	Risk of flood	.23
		(.15)
	Farmer's vulnerability	-02
		(.05)

Note: We report standard errors in parentheses. *significant at 10% level; **significant at 5% level.

To investigate the robustness of the results[22] to the possible hidden bias, we run a sensitivity analysis by computing the Rosenbaum bounds. The results, presented in Table 5, reveal that under the assumption of no hidden bias ($\Gamma = 1$), the treatment effect on all three outcomes[23] is significant. For the case of possible hidden bias ($\Gamma > 1$), the odds ratio of treatment assignment between treatment and control groups should differ by at least 35% under the influence of the hidden bias in order to undermine the results of our analysis. Specifically, for on-farm employment, the hidden bias has to be as strong to cause the odds ratio of treatment assignment to differ by 1.35:1. This ratio for female engagement in farming has to be at least 1.37:1 and for employing improved seeds and crop varieties 1.36:1.

It is important to note that Rosenbaum bounds are the worst-case scenarios. A small significant value of Γ does not mean that there is no positive treatment effect; it only states that the confidence interval for the project effect would contain zero (Becker & Caliendo, 2007). In our case, however, the (significant) values of Γ for all three outcomes are reasonably high.

Table 5. Rosenbaum bounds for LDCF project treatment effects.

Outcome variable	ATT	Gamma (**Γ**)	p-critical*
On-farm employment (Fem)**	.38	1	0.006
		1.1	0.018
		1.2	0.044
		1.3	0.082
		1.4	0.152
Women engagement in farming**	.32	1	0.004
		1.1	0.014
		1.2	0.033
		1.3	0.067
		1.4	0.118
Use of improved seeds and crop varieties***	.12	1	0.008
		1.1	0.021
		1.2	0.044
		1.3	0.080
		1.4	0.129

*for positive treatment effects
**rbounds command is used to compute the Rosenbaum bounds
***mhbounds command is used to computer the Rosenbaum bounds

[22] of the outcomes for which significant project impact is observed.

23 On-farm employment, female engagement in farming, and use of improved types of seeds and crop varieties.

6. Discussion

Our findings, which are summarized in Table 4, suggest that the LDCF project caused significant positive impact on adaptation outcomes such as female engagement in farming, on-farm employment, and use of improved types of seeds and crop varieties. However, no significant project impact on outcomes like risk of drought, risk of flood, and overall farmers' vulnerability to climate change was observed.

This study examined the engagement of females in farming by analyzing the number of females (per household) involved in agriculture activities (such as bee-keeping, gardening, planting and harvesting, and packaging[24]). Our findings show that on average more females are engaged in various farming activities among those households benefited from the project. Involving females in adaptation practices is crucial as they are playing a key role in rural economy and agriculture production[25]—for instance, Chandra, et al., 2017 found that worldwide about 43% of labor in rural areas (where farming is the main employment) is provided by females (in our sample this average per household is 44%).

Similarly, we investigated the on-farm employment by analyzing the number of household members working on the farm. Our results suggest that on average more family members are employed in farming activities among treated households. It is certain that agriculture is the mainstay of rural economy contributing to livelihood, food security, and employment. The sector is affected by climate change and prolonged drought across Afghanistan (WFP; UNEP; NEPA, 2016). Among other consequences, farming practices have mostly reduced which in turn caused significant drop in on-farm employment. A latest World Bank's report[26] confirms that unemployment rate is particularly high amongst low-skilled, illiterate workers. Considering the fact that farmers have a slim chance of employment in other sectors (they are generally illiterate with low professional skills), it is important to restore and expand on-farm employment through adaptation measures that boost farming practices.

Crop diversification and the use of improved types of seeds, considering the traditional way of farming at the study sites, can serve as an effective adaptation strategy to the changing climate—as recommended by previous research (Makate, et al., 2016; Lin, 2011). The current

24 Fact sheet of the project for Bamiyan and Daikundi provinces.

25 Supporting females participation in production activities not only essential for providing labor and increasing production but also help communities to meet the Goal 5 (Achieve gender equality and empower all women and girls) of the UN's Sustainable Development Goals (SDGs).
http://www.un.org/sustainabledevelopment/gender-equality/

26 http://www.worldbank.org/en/country/afghanistan/overview

research examined the use of improved types of seeds and crop varieties by analyzing the number of households that employed such measures. Our results suggest that the number of farmers implemented these strategies is significantly higher in treated communities. It is important to note that the treated farmers were provided with improved types of seeds and fruit trees (including almond, apricot, caraway, and alfalfa) and were consulted on using different crop varieties that are drought-tolerant and have high adaptive capacity to climate change.

Certainly drought and flood are the most severe weather events that are related to climate change and relentlessly affected the farmers across Afghanistan. The risks of both events are expected to increase as a result of climate change and variability (WFP; UNEP; NEPA, 2016). In fact, addressing the risks of drought and flood (by improving water resources and watershed management) was the main target of the LDCF project (Baizayee, et al., 2014). In this research we investigated the risks of both events by assessing the farmers' perception in both treated and non-treated communities. Our estimates show no significant difference in perceived risks of drought and flood among farmers in the two groups. A similar result was found in vulnerability of the farmers to climate change. Our findings suggest that the farmers in both groups are equally vulnerable to the impacts of climate change.

Additional evaluation of the two groups of outcomes—outcomes for which significant project impact was observed[27]; and otherwise[28]—reveals that the outcomes within each group are similar in terms of their capacity to be influenced by exogenous factors. A comparison of the magnitude of risks of drought and flood to the size and length of the intervention, for example, shows that the LDCF project is—by distance—limited to address these risks in full. On the other side, the outcomes such on-farm employment and use of improved types of seeds can be influenced rather fast and by relatively narrow interventions.

It is necessary re-emphasizing that current study is limited to evaluate the community level impact of the LDCF project in Bamiyan and Daikundi provinces. To have an overall understanding of the community level impacts of the project, similar investigation should be carried out in Badakhshan and Balkh provinces.

7. Conclusion

Understanding the importance of project evaluation, in particular for pilot interventions, this paper aimed to examine the impacts of the first climate change adaption (pilot) project in

27 On-farm employment, females' engagement in farming, and use of improved types of seeds.

28 Risks of drought and flood and overall farmers' vulnerability to climate change.

Afghanistan, supported under the Least Developed Countries Fund (LDCF). We use a field survey dataset and two propensity score-based estimators (nearest neighbor matching and inverse propensity score weighting) to evaluate the community level impacts of the project in Bamiyan and Diakundi provinces. Specifically, we investigated the impact of the project on adaptation related outcomes such as on-farm employment, females engagement in farming, use of improved types of seeds and crop varieties, risks of drought and flood, and overall farmers' vulnerability to climate change.

Our findings suggest positive project impact on outcomes such as on-farm employment (about 15%), females' engagement in farming (about 23%), and use of improved types of seeds and crop varieties (almost 11%). The results, however, do not show any significant project impacts on risk of drought, risk of flood, and overall farmers' vulnerability to climate change.

Overall our findings imply that while the project has been a successful outset for climate change adaptation; to address the existing and expected climate change-related risks, it is recommended that a long-term full-size intervention at the study sites should follow.

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Appendix A – Additional Figures and Tables

Table A.1: CDCs and sample distribution.

No.	District	Valley	CDC	Category	Total number of households	Sample
1T	Bamiyan Center	Seya Layak	Seya Layak	Treated	281	10
2T	Bamiyan Center	Borghoso	Borghoso&Ali Big	Treated	104	9
3T	Bamiyan Center	Qazan	Qazan, Ab Bala	Treated	370	10
4T	Bamiyan Center	Qazan	Kharaba	Treated	112	8
5T	Bamiyan Center	Saadat/Chap dara Pitaw	Kholankash-Jawkar	Treated	100	11
6T	Bamiyan Center	Khushkak	Khushkak-e-Bala	Treated	46	5
7T	Bamiyan Center	Khushkak	Olang-Qabr Zaghak	Treated	40	5
8T	Bamiyan Center	Dokani	Jaw Zari	Treated	86	10
9T	Bamiyan Center	Somara	Sar-e-Somara	Treated	61	10
10T	Bamiyan Center	Ahangaran	Sar-e-Ahangaran 2	Treated	231	7
11T	Nili	Nili	Sar Qol-e-Sangmom	Treated	60	5
12T	Nili	Nili	PerBagh-e-Dasht	Treated	109	24
Sub-total (treated)					*1,537*	*114*
1C	Bamiyan Center	Seya Layak	Khuja Roshnae	Non-treated	256	9
2C	Bamiyan Center	Borghoso	Borghoso&Ali Big	Non-treated	104	12
3C	Bamiyan Center	Qazan	Naw Joe	Non-treated	245	11
4C	Bamiyan Center	Qazan	Seya Khak	Non-treated	70	5
5C	Bamiyan Center	Saadat/Chap dara Pitaw	Kholankash	Non-treated	156	9
6C	Bamiyan Center	Khushkak	Rashak	Non-treated	50	5
7C	Bamiyan Center	Khushkak	Olang-Sorkhak Tangi	Non-treated	35	5
8C	Bamiyan Center	Dokani	Horgosh	Non-treated	58	11
9C	Bamiyan Center	Somara	Somara	Non-treated	138	11

10C	Bamiyan Center	Ahangaran	Sar-e-Ahangaran 1	Non-treated	132	6
11C	Nili	Nili	Ghroj-e-Sangmom	Non-treated	72	6
12C	Nili	Nili	Zanborkhana-e-Dasht	Non-treated	154	31
Sub-total (non-treated)					*1,470*	*121*
Grand-total					3,007	235

Appendix B – English Translation of the Survey Instrument

Section	Question/Instrument description [Abbreviation]	Values
Valley/CDC	District	1-Nili; 0-Bamiyan center
	Valley [CDC]	1-Nili; 2-Seyalayak; 3- Borghoso; 4 &5-Qazan; 6- Saadat/Chap dar-ePitaw; 7-Khushkak; 8-Dokani; 9-Somara; 10-Ahangaran
	Is your farmland flat?	1-Yes; 0-No
	Does a river flow form your village?	1-Yes; 0-No
	Do you have access to a road?	1-Yes; 0-No
Personal/household	Gender	1-Male; 0-Female
	Marital status	1-Married; 0-Single
	Age (in years) [Age]	
	Farming experience (in years) [FarmingEx]	
	Main Job [MainJob]	0-Farming; 1-Housework; 2-Self-employed other than farming; 3-Others
	How many of household members are employed on farm? [FarmE]	
	How many of the female members work on farm? [FwonF]	
Wealth/Farm and Irrigation	In 24 hours, how many hours do you have electricity? [HrsEl]	
	How many cars do you own? [Car]	
	How much is the size of your farm? [Farmsize]	
	Is the irrigation water comes from a river? [IrWRiver]	1-Yes; 0-No
	Is the irrigation water comes from a Stream? [IrWStream]	1-Yes; 0-No
	Is the irrigation water comes from a Karez? [IrWKarez]	1-Yes; 0-No

	Do you consider the limited farm land as a constraint towards farming and adaptation? [FCSmallFland]	1-Yes; 0-No
	Do you consider the poor soil fertility as a constraint towards farming and adaptation? [FCSmallFland]	1-Yes; 0-No
Climate Change Perception	In your opinion, what is the main cause of climate change? [CCC]	0-God's will; 1-Nature; 2-Human
	In your opinion, has the average temperature increased during last 15-20 years? [Tem]	1-Increased; 0-Otherwise
	In your opinion, has the average precipitation decreased during last 15-20 years? [Pre]	1-Decreased; 0-Otherwise
Adaptation to Climate Change	Have you been using improved types of seed and crop varieties in recent years? [AdptImS]	1-Yes; 0-No
	Were you covered by LDCF project? [LDCF]	1-Yes; 0-No
	In your opinion, has the LDCF project been effective? (Answer this question only if the answer to the previous question is "Yes") [RateLDCF]	1-Effective; 0-Otherwise
Climate change Risk and Vulnerability	In your opinion, how serious is the risk of drought? [Rdrought]	1-Not serious at all; 2-Not serious; 3-Somhow serious;4-Serious; 5- Very serious
	In your opinion, how serious is the risk of flood? [Rdrought]	1-Not serious at all; 2-Not serious; 3-Somhow serious;4-Serious; 5- Very serious
	Do you consider yourself (including family and farming) vulnerable to the impacts of climate change? [FarmV]	1-Yes; 0-No