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Adaptation Implications of Climate-Smart Agriculture in Rural Pakistan

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Abstract: In this paper, we analyze the drivers of the adoption of climate-smart agricultural (CSA) practices and the impact of their adoption on farm net returns and exposure to risks. We use recent farm-level data from three agroecological zones of Pakistan to estimate a multinomial endogenous switching regression for different CSA practices used to reduce the adverse impact of climate change. These strategies include changing input mix, changing cropping calendar, diversifying seed variety, and soil and water conservation measures. The empirical results show that the adoption of different CSA practices is influenced by average rainfall, previous experience of climate-related shocks, and access to climate change information. The findings further reveal that adoption of CSA practices positively and significantly improves farm net returns and reduces farmers' exposure to downside risks and crop failure. The results also reveal significant differences in the impacts of CSA practice adoption on farm net returns in different agroecological zones. Thus, policies aimed at achieving sustainability in agricultural production should consider agroecological, specific, climate-smart solutions.

Keywords: climate change; CSA adoption; impact assessment; household welfare; Pakistan

JEL Classification: C21; Q54; O33

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1. Introduction

Severe climate change is making the global weather uncertain and is having a devastating effect on agriculture [1–3]. Warm atmospheres, decreases in snowfall, rising sea levels, unpredicted changes in precipitation, and greenhouse gas emissions are causing extreme weather and climatic events [4]. The temperature rise is the major driver of such changes [5]. Climate change and extreme weather events are major threats to agriculture around the world, especially in South Asian countries. Climate variability induces challenges to achieving food security, poverty reduction, and rural development in these countries due to the vagaries of weather [6,7] and other natural disasters such as extreme temperatures, extremely erratic rainfall, floods and droughts, dust cyclones, pest infestation, and crop diseases coupled with low adoption rates of new technologies [8]. Variations in climate have a significant impact on water resources, agriculture production, food supply, farmers' wellbeing, and finally the global economy [9].

Climate-smart agriculture (CSA) has emerged as a framework for developing and implementing robust agricultural systems, which simultaneously improve food security, living conditions in rural areas, facilitate adaptation to climate change, and provide mitigation benefits [10]. The global community has recommended the incorporation of climate-smart agriculture (CSA) practices into national development plans to mitigate the adverse impacts of climate change on agriculture [11]. Climate-smart agriculture practices include practices that sustainably increase agricultural productivity, adapt and build the resilience of agricultural and food systems to climate change, and tend to reduce greenhouse gas emissions from agroecosystems [10]. CSA practices such as changing input mix and cropping calendar, crop diversification, diversifying seed variety, crop rotation, soil and water conservation, using improved seed variety, income diversification, crop and livestock integration, and improving irrigation efficiency are strategies generally used to reduce climate change adverse effects [12–14].

It is projected that by the middle of the 21st century, the largest number of food-insecure people will be found in South Asia due to the adverse effects of climate change [8]. Previous studies have shown that the adoption of CSA practices plays a significant role in increasing farm productivity and household income and contributing to poverty reduction and food security [13,15–17]. Moreover, the adoption of CSA practices has been found to help smallholder farmers living in rural areas overcome production and income risks [18–20]. For these reasons, the significance of promoting farm households' adoption of CSA practices to improve their livelihood welfare has attracted considerable attention from researchers and policymakers.

Most of the empirical studies on adoption of CSA practices are focused on countries in sub-Saharan Africa [21–26], with few studies on Asian countries [14–17]. The study by Abid et al. [16] found that adaptation to climate change improves farm productivity and crop income. Despite the potential of CSA practices to enhance agricultural sustainability, adoption rates of CSA practices in Pakistan are reported to be very low. A study by FAO found that the adoption rate of balanced input use, use of drought-tolerant varieties in rain-fed areas, soil and water conservation practices for cotton farmers are less than 30% [27]. The reasons for low adoption rates in Pakistan appear to be mixed. For instance, Salman et al. [28] reported that many farmers in Pakistan do not consider climate change as a potential threat to agriculture and therefore do not see the need to change their farming practices. Besides, policy implementation regarding adaptation to climate change is weak and therefore requires strong integration with other policies, institutions, and funding in support of promoting CSA practices [27,29].

The present study contributes to the growing literature on the adoption of CSA practices by examining the factors that influence the adoption of these practices, as well as estimating the impact of adoption on farm net returns and downside risk exposure. The climate-smart agriculture practices considered in this study include adoption strategies such as changing cropping calendar, diversifying seed varieties, changing input mix, and soil and water conservation [11,15]. We combined spatial climate data with recent survey data of 540 farm households from three important agroecological zones of the Punjab province of Pakistan in the analysis. By following the procedure of Antle [30], we estimate the skewness of farm net returns, which is used as a proxy for downside risk exposure or probability of income risks. An increase in the skewness of farm net returns lowers the probability of crop failure and income risks. We employ a multinomial endogenous switching regression (MESR) model to account for selection bias in a multiple-choice context. We also employ multivariate treatment-effect regression in a sensitivity analysis to ensure the robustness of our results. To the best of our knowledge, this approach has not been applied to analyze climate-smart agricultural practices and production risks in Pakistan.

Since smallholder farmers predominantly cultivate mixed crops as part of risk minimization strategy, we depart from the previous studies that analyzed farm-level risk based on monocropping context [31,32] by considering the multi-cropping nature of farming in Pakistan in our analysis. Furthermore, we examine the factors that influence farmers' choices of different CSA practices, since understanding linkages between these choices and farm outcomes can provide significant information about climate policy, particularly the possible promotion and scale-up of different CSA practices. Analysis of CSA adoption choices may also provide insights into which option is a more effective adaptation strategy for multiproduct farmers facing the threat of climate change. To the extent that CSA overlaps with most development goals such as food security, poverty reduction, and rural development [33], the results obtained from this study can inform climate change policy, especially in developing country settings similar to Pakistan.

The rest of the paper is organized as follows. Section 2 presents materials and methods. Section 3 presents the results and discussion, while Section 4 presents the conclusion and policy implications of the study.

2. Materials and Methods

2.1. Data and Descriptive Statistics

The cross-sectional data used in this study come from a survey conducted between January and March 2017 in three agroecological zones in Pakistan. The data were collected from six administrative units of the Punjab province. Three important zones (cotton zone, rice zone, and mix cropping zone) were selected purposively based on climatic and agroecological cropping patterns (see Figure 1). Overall, 540 farmers, cultivating 748 plots, were interviewed. The face-to-face interviews were conducted with the support of well-trained research assistants who could speak the local language from the study area.

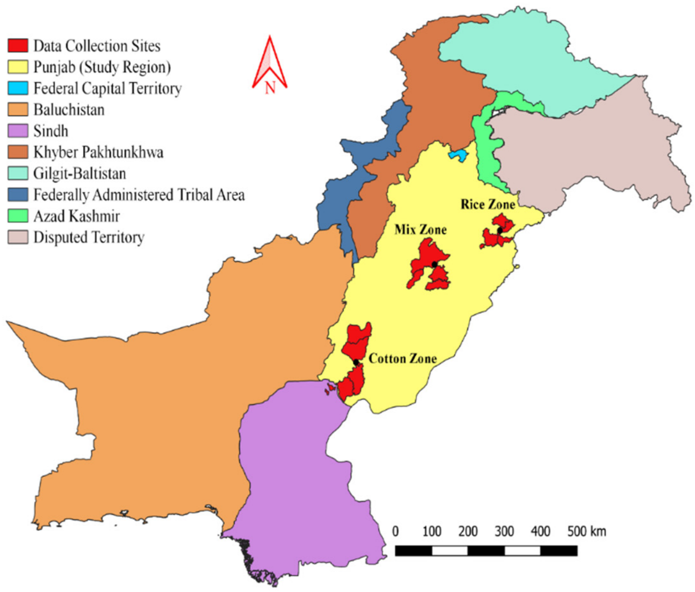

Figure 1. Map of Pakistan showing study area and data collection sites.

The data collected included information on farm households, agricultural practices, production and costs, irrigation water use, access to extension, social networking, perceptions about climate change and climate risks, responses to climate change, credit access, farm and household assets, other income sources, consumption, and expenditure. The data also captured climate change perceptions and climate risks and farmers' adaptation responses. Questions were included to ask the farmers whether they have noticed long-term changes in temperature and precipitation over the last twenty years.

Secondary information related to temperature and rainfall was collected from the National Center for Environmental Prediction (NCEP) and the World Weather Online site. The collected information ranges from 1979 to 2016, the same year in which we conducted the survey. With the help of the GPS data gathered during the survey process, we employed an interpolation method to combine the secondary data with the household survey data. Subsequently, we computed the temperature and rainfall anomalies, taking 2016 as a base year.

The descriptive statistics of key climate-smart agricultural practices and other variables are presented in Table 1. The data indicate that at least one CSA practice was adopted on 46% of cultivated plots, implying that among the four strategies considered in this study, at 54% of plots had none being implemented by farmers. In particular, 11% of plots had diversification of seed variety as a strategy, 14% of plots practiced changing cropping calendar, changing input mix was practiced on 13% of plots, while soil and water conservation measures were adopted on 15% of cultivated plots. Thus, we identify four main climate-smart agricultural strategies namely, (1) seed variety diversification, (2) changing cropping calendar, (3) changing input mix, and (4) soil and water conservation.

Table 1. Definition and descriptive statistics of selected variables.

Variables	Definition	Mean	SD
No adaptation	1 if farmer choose not to adopt CSA, 0 otherwise	0.464	0.499
Seed varieties diver.	1 if farmer adopted seed variety diversification at the farm, 0 otherwise	0.112	0.316
Cropping calendar	1 if farmer adopted a change in sowing dates of crops, 0 otherwise	0.142	0.349
Input mix	1 if farmer adopted change in input mix, 0 otherwise	0.131	0.338
SWC	1 if farmer chose to adopt soil and water conservation, 0 otherwise	0.151	0.358
Credit_const	1 if farmer is credit constrained, 0 otherwise	0.282	0.450
Avg Tem	Average annual daily temperature in (degrees Celsius)	27.334	1.110
Avg Rain	Average annual daily rain (millimeters)	0.639	0.553
Int TxR	Product of average daily temperature and average daily rainfall	16.882	13.821
Tem anomaly	Change in temperature relative to baseline [a] (number)	0.217	0.032
Rain anomaly	Change in rainfall relative to baseline (number)	−0.369	0.194
HH age	Household head age (years)	47.219	11.259
Family size	Number of persons residing in a household (number)	6.147	2.223
Education	Number of schooling years household head completed (years)	6.524	4.293
Plot size	Total number of acres [b] a farm household cultivate at one place (acres)	5.937	3.580
Herd size	Number of animals a farm household owns (number)	4.052	2.360
Machinery	1 if farmer has own farm machinery, 0 otherwise	0.247	0.432
cc_shock	1 if farmer exposed to climate-related shocks in the past three years, 0 otherwise	0.386	0.487
Ext services	1 if farmer has contact with govt. extension agent, 0 otherwise	0.290	0.454
Cotton zone	1 if farmer resides in cotton growing zone, 0 otherwise	0.310	0.463
Rice zone	1 if farmer resides in mix cropping zone, 0 otherwise	0.334	0.472
Mix zone	1 if farmer resides in rice growing zone, 0 otherwise	0.356	0.479
Fertile	Mean fertility = 1 if soil is fertile, 0 otherwise	0.434	0.437
Erosion	Mean erosion = 1 if farm land has moderate to severe erosion, 0 otherwise	0.210	0.532
Plot distance	Mean distance to agricultural plot from farmer's house (km)	2.122	1.421
cc info	1 if a farmer receives current information related to climate change, 0 otherwise	0.373	0.484
cc perception	1 if farmer perceives changes in climate change over the past (20) years, 0 otherwise	0.356	0.479
Net returns	Gross farm revenue minus variable costs (Thousand PKR [c])	59.119	17.569
	Total no. of obs.	748	

[a] Anomaly = (current year mean—long term mean)/long term mean, [b] 1 acre = 0.405 hectare, [c] PKR (Pakistani Rupee) is Pakistani currency (USD 1 = PKR 104.67 during the year of data collection).

Table 1 displays the definitions of the variables and their mean characteristics. On average households are large (6 persons in a household), headed by a male of an average age of 47 years with 6 years average formal education. On average, farmers earn PKR 59 thousand per acre from agricultural plots [USD 1 = PKR 104.67 at the time of data collection]. With a poverty line of PKR 3250 [34], it can be inferred that these farmers are above the poverty line. The average herd size consists of 4 animals owned by a farm household. The average daily temperature and rainfall are recorded at 27 °C and 1 mm over the last 38 years, respectively. Climate shocks are captured as rainfall and temperature anomalies. In Table A7, we report the summary statistics of key variables by agroecological zones considered in this study. There appear to be qualitative differences among key variables across the zones.

We use the moment-based approach proposed by Antle [30] to capture farmers' exposure to risks. The approach accounts for exposure to risks by using the sample moments of farm net returns to capture the skewness, which is the third moment as noted by Huang et al. [35]. With current climate trends, Pakistan is forecast to reach absolute water scarcity by 2025 [36], which could expose farmers to severe production risk and reduction in crop yields. The moment method of risk determination involves regressing farm net returns per acre on production inputs and other socioeconomic variables, after which residuals are predicted. Then, the third central moment of farm net returns (skewness) is computed by raising the residuals to the third power. Figure 2 displays unconditional farm net returns distributions by different CSA practices adopted in the study region. The figure clearly shows negative skewness of farm net returns for non-adopters compared to adopters of CSA practices.

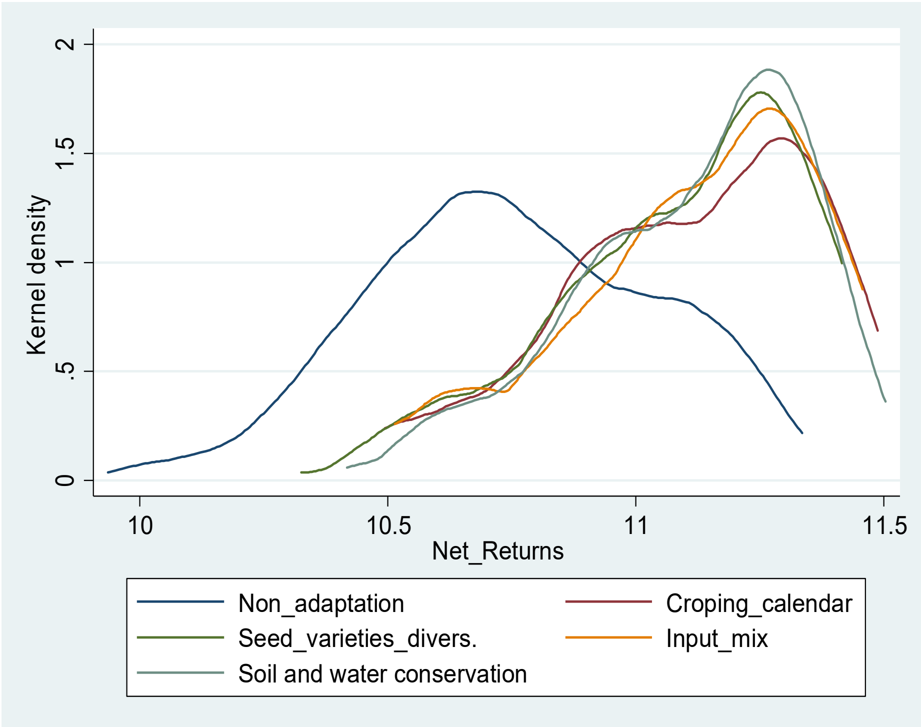

Figure 2. Unconditional farm net returns distributions by CSA practices.

2.2. Conceptual Framework

The conceptual framework used in the analysis assumes that farmers normally adopt CSA practices to minimize the adverse effects of climate change. We assume a multiproduct farmer producing under uncertain climate scenarios, with different choices of climate-smart agricultural practices. In this study, the specific CSA practices considered included changing input mix, changes in cropping calendar, diversifying seed variety, and soil and water conservation. Diversification of seed varieties includes the use of drought-resistant and early maturing varieties that enable farmers to cope with erratic rainfall or very low rainfall [37]. Changing the input mix includes changing fertilizer types and quantities, changes in pesticide use, changing irrigation, changing the use of herbicides or weedicides, and micronutrients [38]. Soil and water conservation refers to erosion control and other employed methods to prevent soil and nutrient loss, and conserve soil moisture. These include crop rotation, sowing cover crops to fix nitrogen in the soil, planting on ridges, making soil to reduce soil erosion and water loss, and use of farmyard manure with minimum tillage to increase the soil's water-holding capacity [39,40].

We assume that farmers are risk-averse and consider farm net benefits from the adoption of CSA practice on their plot in their decision-making processes. The farm net benefits considered in the present study is farm net returns (π_i) from multiple crops, derived under inputs mix (I) and adaptation strategies (A) at a cost. The farmer is assumed to be using a production technology that is continuous, concave, and at least twice differentiable. The farmer's production function can be represented as $Q = f(I, A, e)$, where e is a vector of stochastic factors unknown to the farmer when production decisions are made. The vector e is treated as a random variable, whose distribution is exogenous to farmers' actions [19,41]. Hence, e captures the climate risks under imperfect predictability of farm net returns beyond farmers' control (such as extreme temperature, erratic rainfall, floods and droughts, production losses due to pest infestation and diseases). In the short term, farmers are price takers, so the assumption related to the non-randomness of output and input prices is not critical [42]. Therefore, we assume that output prices, input, and technology adoption costs are nonrandom and are known to the farmer when production decisions are made.

With the above-given assumptions, the farmer is assumed to maximize expected farm net returns as follows:

$$max\ E[U(\pi_i)] = maxE\left[U\left\{\left(\sum_{n=1}^{N} p_n Q_n\left(I_n, A_j,\ e\right)\right) - \sum_{n=1}^{N} w_n I_n - \sum_{j=2}^{M} w_j A_j\right\}\right] \quad (1)$$

where π_i is the farm net returns obtained from plot i, E is an expectation operator, Q_n and p_n are the output quantity and output price of nth crop, respectively, w_n is a vector of input prices and I_n is the vector of inputs used, w_j is the vector of prices incurred in adopting jth CSA practice and A_j is the jth practice from a combination of CSA practices. We consider $(j = 1)$ as a reference category, i.e., non-adoption. We assume that the farmer compares the farm net returns from adopting jth CSA practice A_{ij}^{a} for plot i and the farm net returns obtained from non-adoption A_{i1}^{n}. A risk-averse farmer will adopt jth CSA practice if the expected utility of farm net returns from adoption $E[U(A_{ij}^{a})]$ is greater than the expected utility from adoption $E[U(A_{i1}^{n})]$. This can be expressed as $E[U(A_{ij}^{a})] - E[U(A_{i1}^{n})] > 0$.

2.3. Empirical Strategy

In the empirical analysis, we analyze the decisions of farmers to adopt different CSA practices, using a multinomial endogenous switching regression (MESR) approach. The MESR model is a two-step estimation procedure that considers selection bias correction among all alternate choices in question [32,43]. In the first step, factors affecting the adoption of CSA practices are considered. In the second step, consistent estimates of parameters of all explanatory variables of interest are estimated to identify the impacts of these variables on the outcomes of interest (mean farm net returns and exposure to risk captured by the skewness of farm net returns).

2.3.1. The Multinomial Endogenous Switching Regression Model

As mentioned above, the farmer adopts CSA practices if the expected farm net benefits from adoption are positive. Given that the expected farm net benefits cannot be directly observed, we represent it with a latent variable A_{ij}^{*} which can be expressed as a function of observed (Z_i) and unobserved (ζ_{ij}) characteristics as follows:

$$A_{ij}^{*} = Z_i\gamma_j + \zeta_{ij} \quad (2)$$

where j represents different CSA practices, such that $j = 1, 2, 3, \ldots, M$. Additionally, let A_i be an index of a set of CSA practices choices that a farmer can decide to implement on plot i to maximize farm net returns, such that:

$$A_i = \begin{cases} 1 \text{ iff } A_{i1} > \underset{k\neq 1}{max}(A_{ik}^{*})\ or\ \varepsilon_{i1} < 0 \\ \vdots \qquad\quad \vdots \qquad\qquad \vdots \\ M \text{ iff } A_{iM} > \underset{k\neq M}{max}(A_{ik}^{*})\ or\ \varepsilon_{iM} < 0 \end{cases} \quad (3)$$

where $\varepsilon_{ij} = \max\limits_{k\neq j}(A_{ik}^{*} - A_{ij}^{*}) < 0$. From Equation (3), it is obvious that a farmer will implement jth CSA practice on ith plot if the selected practice provides greater expected farm net benefits than any other alternate option $k \neq j$.

It is important to state that Equation (2) includes the deterministic component $Z_i\gamma_j$ and an idiosyncratic component ζ_{ij}. The latter captures the variables that a farm household takes into account when making adoption decisions, but these factors, which include farming skills, the motivation for adoption of CSA practices, cognitive and innate abilities are unknown to the researcher. We can interpret these factors as the unobserved individual propensity of adoption. The deterministic component (Z_i) includes the factors that affect the likelihood of selecting CSA practice j, such as farm household characteristics (e.g., age, education, family size), the ownership of assets such as herd size and farm machinery, location of the farm (rice zone, cotton zone, and mixed cropping zone), past climatic factors (e.g., average rainfall and temperature, extreme temperature and rainfall as anomalies), the experience of extreme weather events captured as past climatic shocks (such as floods, droughts, pest infestation, and diseases), institutional variables such as contact to extension services and liquidity constraints. To account for unobserved heterogeneity at the plot level, we also include in the vector $\overline{Z}_i$ plot-specific characteristics such as mean soil fertility, mean soil erosion and mean plot distance from farmer's house [31].

We assume from Equation (2) that ζ_{ij} are independently and identically Gumbel distributed (so-called independence of irrelevant alternatives (IIA) assumption), we then specify the multinomial logit model as below:

$$P_{ij} = P\left(\varepsilon_{ij} < 0 \middle| Z_i, \overline{Z}_i\right) = \frac{\exp\left(Z_i\gamma_j + \overline{Z}_i\partial_j\right)}{\sum_{k\neq 1}^{M}\exp\left(Z_i\gamma_k + \overline{Z}_i\partial_k\right)}, \text{ where } j = 1, 2, 3, \ldots, M \tag{4}$$

The farmer chooses CSA practice j among any other alternative k, if and only if $A_{ij} > max_{k\neq j}(A_{ik})$. By using this expression, consistent maximum-likelihood estimates of γ_j and ∂_j can be obtained. Furthermore, we perform a Wald test of the joint significance of ∂_j to determine the effect of plot-level heterogeneity or the Mundlak effect [44].

To examine the impact of adoption of CSA practices on the outcome variables, we assume that outcomes from multi-crop production are a linear function of the vector of explanatory variables. We specify the outcome function as:

$$\begin{array}{c} \text{Regime 1}: \; y_{i1} = X_i\beta_1 + \overline{X}_i\theta_1 + +\mu_{i1}, \text{ if } A_i = 1 \\ \vdots \\ \text{Regime M}: \; y_{iM} = X_i\beta_M + \overline{X}_i\theta_M + \mu_{iM}, \text{ if } A_i = M \end{array} \tag{5}$$

where y_{iM} is the outcome of interest (farm net returns or skewness of farm net returns distribution) from the adoption of CSA practice M among different alternatives, β and θ are the parameters to be estimated, μ_i is the error term with zero mean and constant variance, i.e., $\mu_{ij}(0, \sigma^2)$. The vector X_i contains all control variables of interest such as farm and household level characteristics. The vector $\overline{X}_i$ comprises mean soil fertility, mean soil erosion, and mean household distance to the farm plot, which is also included in $\overline{Z}_i$.

As indicated previously, we employ the MESR model proposed by Bourguignon et al. [43] to correct for selection bias from farmers' self-selecting into the adoption of CSA practices. This model considers the potential correlation between the error terms ζ_{ij} in Equation (2) and μ_{ij} in Equation (5). Following Bourguignon et al. [43], we derive the selection bias-corrected equations, which can be used to estimate the consistent β_j in Equation (5). The selection bias-corrected equations can be specified as follows:

$$\begin{array}{c} \text{Regime 1}: \; y_{i1} = X_i\beta_1 + \overline{X}_i\theta_1 + \sigma_1\left[\rho_1 m(P_{i1}) + \sum_{j=2}^{M}\rho_j m\left(P_{ij}\right)\frac{P_{ij}}{P_{ij}-1}\right] + \omega_{i1} \text{if } A_i = 1 \\ \vdots \quad \vdots \quad \vdots \quad \vdots \\ \text{Regime M}: \; y_{iM} = X_i\beta_M + \overline{X}_i\theta_M + \sigma_M\left[\rho_1 m(P_{i1}) + \sum_{j=2}^{M}\rho_j m\left(P_{ij}\right)\frac{P_{ij}}{P_{ij}-1}\right] + \omega_{iM}, \text{ if } A_i = M \end{array} \tag{6}$$

where $\lambda_{ij} = \sum_{j\neq 1}^{M}\rho_j\left[m(P_{i1}) + m\left(P_{ij}\right)\frac{P_{ij}}{(P_{ij}-1)}\right]$ refers to the inverse mills ratio, $m(P_{i1})$ and $m\left(P_{ij}\right)$ are conditional expectations of ζ_{i1} and ζ_{ij}, which are used to correct selectivity bias, ρ_j is the coefficient of correlation between μ_{ij} and ζ_{ij}, σ_j is the standard deviation of disturbance terms from net returns equations, and ω_i is the error term.

To ensure model identification, we use access to climate change information and perception of climate change as instrumental variables. Access to climate-specific information is expected to enhance farmers' understandings about climate change and directly influence their adoption decisions. Similarly, perceptions and expectations of future events may shape behavior, feelings, and thoughts [45,46] and are assumed to be good predictors of economic behavior. We performed a Wald test to assess the admissibility of these instrumental variables. Another issue that deserves attention is the potential endogeneity of extension contact and credit constraints variables in the selection equation. The test results of the validity of these instruments are presented in the Appendix (see Tables A2 and A3). This is because extension service officers may provide information related to particular CSA practices, and farmers adopt these practices against climate change for better farm production [47]. The credit constraints variable is potentially endogenous because non-adopters may be more prone to lower incomes, which worsen their creditworthiness, and hence their liquidity status. This study applies the control function approach suggested by Murtazashvili and Wooldridge [48] to account for potential endogeneity arising from these variables.

2.3.2. Counterfactual Analysis and Average Treatment Effects on the Treated (ATT)

Following Heckman et al. [49], we estimated the treatment effects on the treated. We compared the farm net returns of adopters to their counterfactual farm net returns if they had not adopted. Therefore, the conditional expectations for each outcome variable based on CSA practices chosen ($j = 2, \ldots, M$ with $j = 1$ as the base category) can be stated as follows:

$$\begin{array}{c} E(y_{i2}|A_i = 2) = X_i\beta_2 + \overline{X}_i\theta_2 + \sigma_2\lambda_{i2} \\ \vdots \qquad \vdots \qquad \vdots \\ E(y_{iM}|A_i = M) = X_i\beta_M + \overline{X}_i\theta_M + \sigma_j\lambda_{iM} \end{array} \tag{7}$$

The counterfactual case that adopters did not adopt CSA practices ($j = 1$) can be stated as:

$$\begin{array}{c} E(y_{i1}|A_i = 2) = X_i\beta_1 + \overline{X}_i\theta_1 + \sigma_1\lambda_{i2} \\ \vdots \qquad \vdots \qquad \vdots \\ E(y_{i1}|A_i = M) = X_i\beta_1 + \overline{X}_i\theta_1 + \sigma_1\lambda_{iM} \end{array} \tag{8}$$

The impact of adopting jth CSA practice is denoted as average treatment effects on the treated (ATT), which can be calculated by subtracting Equations (7) and (8) as follows:

$$\begin{array}{c} ATT_2 = X_i(\beta_2 - \beta_1) + \overline{X}_i(\theta_2 - \theta_1) + \hat{\lambda}_{i2}(\sigma_2 - \sigma_1) \\ \vdots \qquad \vdots \qquad \vdots \\ ATT_M = X_i(\beta_M - \beta_1) + \overline{X}_i(\theta_M - \theta_1) + \hat{\lambda}_{iM}(\sigma_M - \sigma_1) \end{array} \tag{9}$$

where the terms $\overline{X}_i(.)$ and $\hat{\lambda}_{i2}(.)$ account for unobserved heterogeneity and selection bias, respectively.

3. Results and Discussion

3.1. Determinants of Adoption of Climate-Smart Agriculture (CSA) Practices

Table 2 presents the results obtained from the multinomial logit model (MNL) indicating the drivers of adoption of CSA practices. The potential endogeneity arising from extension services and credit constraint variables is controlled by using a control function approach. The coefficients of the generalized residuals of extension contact (Res_ext) and credit constraint (Res_Credit) are insignificant in all the CSA practices choices, suggesting that the variables are consistently estimated [48]. In the interest of brevity, the probit estimates of potentially endogenous variables for residuals calculation are reported in the Appendix (see Tables A4 and A5). The results presented in Table 2 show that climate variables positively and significantly affect adoption decisions. The significance of the average rainfall estimate (Avg_Rain) suggests that average rainfall plays a positive role in the adoption of all the CSA practices. The coefficient of the variable climate-related shocks (cc_shock) is positive for all CSA practices, but it is significant for three adoption categories except changing input mix, suggesting that experience of climate-related shocks positively and significantly drives the adoption decision of these CSA practices. The coefficient of the variable representing rainfall anomaly is positive and significant for soil and water conservation (SWC), but is insignificant for all other adoption practices, suggesting that long-term deviations in rainfall tend to increase the probability of adopting soil and water conservation practices. The coefficient of the variable average temperature negatively and significantly influences the adoption decision of changing cropping calendar and soil and water conservation. To account for the combined effect, we also introduced the interaction term between average rainfall and temperature (int_TxR), which is negative and significant for all the CSA practices, indicating that increasing temperature, combined with higher rainfall would negatively and significantly affect adoption decisions. This may be due to the fact that rainfall and temperature are inversely related, therefore, higher rainfalls usually lower the temperature intensity that may result in a negative influence on adoption decisions. This finding is consistent with the study conducted by Deressa et al. [50], who argued that an inverse relationship exists between rainfall and temperature.

Table 2. Determinants of adoption CSA practices, MNLM estimation.

Variables	Seed Variety Diver. (*n* = 98)		Cropping Calendar (*n* = 106)		Input Mix (*n* = 84)		SWC (*n* = 113)	
	Coef.	**St. Err.**	**Coef.**	**St. Err.**	**Coef.**	**St. Err.**	**Coef.**	**St. Err.**
Constant	34.043	(39.395)	64.403 *	(38.316)	26.335	(43.841)	71.299 *	(38.492)
Credit_const	−3.287	(5.013)	−0.494	(4.531)	−2.345	(5.314)	−2.326	(4.671)
Avg_Tem	−1.111	(1.345)	−2.211 *	(1.319)	−1.085	(1.495)	−2.424 *	(1.32)
Avg_Rain	65.521 ***	(24.757)	57.550 **	(23.509)	63.330 **	(26.455)	69.418 ***	(23.423)
int_TxR	−2.663 **	(1.047)	2.461 **	(0.99)	−2.571 **	(1.123)	−2.956 ***	(0.989)
Tem_anomaly	−13.287	(12.059)	−4.902	(11.129)	10.116	(13.395)	3.134	(11.353)
Rain_anomaly	−0.247	(1.757)	1.333	(1.686)	2.048	(1.888)	2.840 *	(1.703)
HH_age	−0.027 *	(0.016)	−0.030 **	(0.015)	−0.008	(0.017)	−0.023	(0.015)
Family size	−0.253 ***	(0.094)	−0.204 **	(0.089)	−0.178 *	(0.093)	−0.229 **	(0.089)
Education	0.085	(0.095)	0.206 **	(0.092)	0.224 **	(0.101)	0.153 *	(0.091)
Plot size	0.047	(0.072)	0.071	(0.066)	0.134 **	(0.067)	0.052	(0.067)
Herd size	0.090	(0.111)	0.032	(0.105)	−0.078	(0.116)	0.020	(0.108)
Machinary	2.240 ***	(0.487)	1.416 ***	(0.483)	2.647 ***	(0.513)	2.034 ***	(0.477)
Ext_services	7.552 *	(3.988)	2.284	(3.977)	4.191	(4.373)	1.703	(3.998)
cc_shock	2.184 ***	(0.638)	1.655 ***	(0.605)	1.042	(0.642)	1.716 ***	(0.598)
Xcotton	−1.489	(1.139)	−0.231	(1.153)	−0.868	(1.249)	0.374	(1.142)
Xrice	−0.568	−0.970	−0.063	(0.935)	−. 1.370	(1.048)	0.441	(0.946)
Fertility	−1.026 *	(0.599)	−0.478	(0.574)	0.635	(0.609)	−0.248	(0.565)
Erosion	−2.314 ***	−0.780	−1.404 *	(0.715)	−1.555 **	(0.781)	−2.608 ***	(0.748)
Plot_distance	−0.375 ***	(0.145)	−0.182	(0.134)	−0.057	(0.147)	−0.103	(0.132)
cc_info	3.623 ***	(0.524)	4.027 ***	(0.504)	4.250 ***	(0.54)	3.829 ***	(0.508)
cc_perception	3.958 ***	(0.512)	3.427 ***	(0.499)	3.900 ***	(0.531)	3.649 ***	(0.498)
Res_Credit	3.654	(3.596)	0.835	(3.184)	3.413	(3.802)	2.546	(3.308)
Res_ext	−4.247	(2.74)	−0.783	(2.706)	−3.548	(2.878)	−0.620	(2.713)
Wald χ^2 for joint sig. of excluded instruments	52.83 ***	[0.000]	51.77 ***	[0.000]	54.54 ***	[0.000]	58.26 ***	[0.000]
Wald χ^2 for joint sig.of plot − level heterogeneity (∂_j)	7.76 *	[0.051]	6.72 *	[0.081]	17.23 ***	[0.000]	13.86 ***	[0.003]
Wald χ^2 for MNL model	768.32 ***	[0.000]						
Pseudo R^2	0.359							
N	748							

Note: Standard errors are given in parentheses. The reference region is mix-cropping zone. The values $p > \chi^2$ are given in square brackets. *** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

The coefficient of the variable education of household head positively and significantly influences the adoption of all CSA practices except seed variety diversification, suggesting that education plays a positive and significant role in the adoption of CSA practices, a finding that is consistent with Huffman [51], who argued that education positively relates to technology adoption decisions in a dynamic and technical environment. The results also showed that ownership of agricultural machinery positively and significantly influences the adoption of all CSA practices. These findings are in line with that of Abdulai and Huffman [23], who argued that ownership of machinery plays a role in the adoption of modern technology. The estimates also show that the coefficient of the variable extension services is positive for all the CSA practices, but is only statistically significant in the adoption of seed variety diversification, indicating that farmers with contact to extension services are more likely to adopt seed variety diversification. The mean plot variant variables also significantly affect adoption decisions [32].

The coefficients of mean plot variant variables (soil erosion, soil fertility, and household distance from cultivated plots) are negative for all the CSA practices, indicating that these factors negatively influence the adoption of CSA practices. Particularly, mean soil erosion and mean household distance from plots, negatively and significantly affect farmers' adoption decisions. A large mean distance from farmers' houses to agricultural plots negatively influences the adoption decisions, probably because farmers require motorized transportation of inputs and operational tasks over long distances. The estimates of climate change information are positive and significant for all the CSA practices, indicating that farmers who have access to climate change information are more likely to adopt CSA practices. Similarly, the coefficient of the variable climate change perception is positive and significant for all CSA practices, suggesting that climate change perception positively and significantly influences all the CSA practices.

3.2. Determinants of Net Farm Revenues and Risk Exposure: Second Stage Estimates of MESR Model

In this section, we explain the economic impacts of adopting CSA practices on farmers' farm net returns. Table 3 presents the second stage results obtained from the MESR model. Similar estimates for downside risk exposure using skewness as the dependent variable are presented in Table A1 in the Appendix. The five types of CSA adoption choices generate five selectivity terms denoted by Mills m1-m5. The results indicate that the selectivity correction terms are significant in some of the CSA practices options (seed variety diversification, input mix, and soil and water conservation (SWC)), indicating that the potential sample selectivity bias has been duly accounted for in the model. For example, the estimates show a negative selectivity coefficient for the adoption of seed variety diversification in the specification explaining the impact of the adoption of soil and water conservation. This finding suggests lower farm net returns for farmers adopting seed variety diversification than randomly chosen farmers due to farmers with better-unobserved attributes shifting from the adoption of seed variety diversification to the adoption of SWC measures.

The results in Table 3 also reveal that the coefficient of the credit constraint variable is negative for all CSA practices, but statistically significant for non-adopters, suggesting that credit-constrained farmers who did not adopt CSA practices obtained lower farm net returns relative to adopters. It also signifies the role of access to credit in enhancing the adoption of CSA practices and farm productivity as found in previous studies [23,50,52]. Ownership of agricultural machinery has a positive effect on farm net returns with only a statistically significant effect for changing cropping calendar and a negative but significant effect for input mix. The significant impact on net revenues for plots with changing cropping calendar option is probably due to farmers' ability to make timely decisions about sowing and harvesting of crops, or access to machinery, which allows for effective implementation of changing cropping calendar to improve farm net returns. The coefficient of extension services has the expected positive and significant impact on farm net returns for adopters and non-adopters of CSA practices, but the magnitude of the impact appears to be higher for adopters.

Table 3. Impact of CSA practices on farm net returns, second stage MESR estimation.

Variables	Non-Adaptation (n = 347)		Seed Variety Diver. (n = 98)		Cropping Calendar (n = 106)		Input Mix (n = 84)		SWC (n = 113)	
	Coef.	**St. Err.**	**Coef.**	**St. Err.**	**Coef.**	**St. Err.**	**Coef.**	**St. Err.**	**Coef.**	**St. Err.**
Constant	−22.040	(91.411)	926.028 *	(502.231)	306.605	(261.090)	573.443	(365.026)	620.694 **	(280.041)
Credit_const	−16.353 ***	(5.081)	−14.874	(22.116)	−20.818	(18.759)	−41.035	(26.981)	−23.331	(15.599)
Avg_Tem	3.202	(3.164)	−28.666 *	(17.004)	−7.553	(8.877)	−14.268	(11.724)	−19.622 **	(9.819)
Avg_Rain	8.381	(64.391)	256.495	(227.868)	198.172	(164.616)	64.965	(238.366)	164.098	(177.373)
int_TxR	−0.033	(2.668)	−13.128	(9.624)	−8.775	(6.753)	−3.844	(9.749)	−8.562	(7.372)
Tem_anomaly	−80.827 ***	(27.670)	−77.572	(130.667)	−14.378	(103.225)	−207.901 *	(124.103)	−47.307	(103.685)
Rain_anomaly	2.211	(3.675)	11.333	(21.066)	14.202	(14.275)	−16.780	(16.654)	13.988	(21.934)
HH_age	−0.055	(0.036)	−0.162	(0.134)	0.036	(0.108)	−0.317 **	(0.131)	−0.170	(0.114)
Family size	0.204	(0.182)	0.018	(0.808)	−0.166	(0.493)	−0.606	(0.688)	−0.480	(0.720)
Education	−0.158	(0.342)	−1.366	(0.850)	−1.157 *	(0.654)	−1.828 *	(1.016)	−1.630 **	(0.789)
Plot size	0.447 ***	(0.167)	−0.235	(0.491)	−0.600	(0.515)	−0.121	(0.613)	0.212	(0.506)
Herd size	−0.533 **	(0.248)	−0.027	(0.870)	0.525	(0.640)	0.675	(0.713)	−0.408	(0.829)
Machinery	4.347	(2.745)	4.606	(3.833)	9.351 ***	(3.427)	−2.065	(3.583)	1.329	(2.874)
Ext_services	21.307 ***	(5.082)	23.046 *	(12.721)	20.965 *	(12.028)	42.297 ***	(15.330)	30.390 **	(12.441)
cc_shock	−1.629	(2.059)	1.382	(7.858)	1.800	(6.316)	12.974	(8.820)	5.431	(5.651)
Xcotton	−7.261 **	(2.836)	19.974	(15.470)	7.505	(9.768)	0.675	(11.893)	16.477	(10.930)
Xrice	4.637 ***	(1.720)	21.853 *	(11.154)	12.916 *	(7.397)	12.144	(11.078)	19.584 **	(9.618)
Fertility	3.124 ***	(1.152)	13.590 **	(6.444)	8.273	(5.443)	−2.544	(4.808)	4.131	(4.643)
Erosion	−0.202	(2.022)	−2.319	(7.152)	−6.353	(5.669)	2.307	(6.522)	−7.270	(7.407)
Plot_distance	−0.632 **	(0.295)	0.933	(1.896)	0.316	(1.224)	−3.016 **	(1.521)	−0.503	(1.213)
_m1	−3.661	(4.965)	1.982	(16.644)	−5.384	(10.388)	−11.388	(13.121)	−4.952	(10.154)
_m2	−0.267	(12.199)	−7.152	(8.376)	−9.512	(15.486)	4.841	(15.408)	−35.164 *	(18.247)
_m3	10.304	(14.344)	−18.312	(26.957)	−8.613 *	(5.210)	40.730 *	(21.818)	−4.690	(22.033)
_m4	−1.982	(17.417)	−26.883	(26.507)	−10.414	(15.333)	−19.788 ***	(7.511)	−46.403 ***	(17.656)
_m5	−16.645	(19.307)	34.798	(28.763)	30.306	(23.434)	−12.345	(25.397)	14.439 *	(7.394)

Note: Bootstrapped standard errors are in parenthesis. The reference region is a mix-cropping zone. *** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

3.3. Impact of Adoption of Climate-Smart Agricultural Practices on Farm Net Returns and Risk Exposure

We also use a counterfactual analysis to examine the impact of CSA adoption on farm net returns. We split the analysis into overall treatment effects and location-wise treatment effects. Table 4 presents the results for overall treatment effects on the treated (ATT) for farm net returns and risk exposure. For robustness check, we also ran a multivariate treatment effects regression to examine the impact of CSA practices on farm net returns and risk exposure [28,53] and compared it with that of the MESR (see Table A6). It shows the expected farm net returns under the observed cases in which farmers adopted CSA practices and in counterfactual cases if they did not adopt CSA practices. The results reveal that farmers who adopted seed variety diversification earned PKR 16,125 higher farm net returns per acre than their counterparts that did not adopt practices, resulting in an increase in farm net returns by about 31% for adopters. In the same way, adopters of changing cropping calendar, on average, earned PKR 15,212 higher farm net returns compared to non-adoption, indicating an increase of 29%. Farmers who adopted an input mix, on average earned PKR 16,185 higher farm net returns compared to non-adopters, indicating a positive change of 31%. These findings are in line with Teklewold et al. [25], who found that adoption of CSA strategies either in isolation or in combination, significantly improved farm net returns in Ethiopia.

It is clear from Table 4 that downside risk exposure of plots with CSA practices was significantly declined. In particular, seed variety diversification reduced the downside risk exposure by 200%, changing cropping calendar by 167%, changing input mix by 300%, and soil and water conservation by 250%. These findings signify the role of CSA practices in minimizing the exposure of farmers to production risks, through a reduction in the probability of crop failure.

Table 4. Overall average treatment effects of adoption of CSA practices.

Adaptation Strategies	Adopters	Non-Adopters	ATT	St. Err.	%Age Change
	Mean1	Mean0			
Farm net returns					
Seed variety diver.	68.543	52.419	16.125 ***	(0.700)	30.76
Cropping calendar	67.118	51.906	15.212 ***	(0.567)	29.31
Input mix	68.570	52.384	16.185 ***	(0.649)	30.90
Soil and water conservation	68.810	52.451	16.359 ***	(0.647)	31.19
Downside risk exposure					
Seed variety diver.	0.001	−0.001	0.002 **	(0.001)	200
Cropping calendar	0.002	−0.003	0.005 ***	(0.001)	167
Input mix	0.002	−0.001	0.003 **	(0.001)	300
Soil and water conservation	0.003	−0.002	0.005 ***	(0.001)	250

*** Significant at 1% level, and ** significant at 5% level.

To the extent that cropping zones are heterogeneous in climatic conditions, we further analyze the differential impacts by cropping zones. Table 5 shows the ATT results by location of cropping zones. It is clear from the table that cotton zone farmers obtained higher farm net returns in all the CSA practices than the other zones, except the input mix option, which is higher in the mix-cropping zone. Farmers who adopted input mix as a CSA practice in the mix-cropping zone earned higher farm net returns than the other two climatic zones. In particular, the adoption of seed variety diversification has the highest (42%) positive and significant effect on farm net returns in the cotton zone. Changing input mix in the cotton zone exerts a positive and significant effect on farm net returns. In the mix-cropping zone, soil and water conservation and changing input mix significantly increase farm net returns by 37%, seed variety diversification and changing cropping calendar improve farm net returns by 31% and 30%, respectively. In the rice zone, seed variety diversification, changing cropping calendar, changing input mix, and soil and water conservation significantly increase farm net returns by about 26%, 24%, 26%, and 25%, respectively. These results generally indicate that CSA practices can play a significant role in raising farmers' incomes, irrespective of the agroecological zone.

Table 5. Average treatment effects of adoption of CSA practices by location.

Zones	Adaptation Strategies	Adopters	Non-Adopters	ATT	St. Err.	%Age Change
		Mean1	Mean0			
Cotton zone	Seed variety diversification	59.154	42.169	16.985 ***	(1.399)	40.28
	Cropping calendar	57.314	40.990	16.324 ***	(1.252)	39.82
	Input mix	57.361	42.485	14.876 ***	(1.262)	35.01
	Soil and water conservation	59.811	42.800	17.012 ***	(1.438)	39.75
Mix zone	Seed variety diver.	62.357	47.698	14.659 ***	(1.188)	30.73
	Cropping calendar	61.416	47.384	14.032 ***	(0.910)	29.61
	Input mix	64.353	47.045	17.307 ***	(1.204)	36.79
	Soil and water conservation	61.678	45.062	16.616 ***	(1.339)	36.87
Rice zone	Seed variety diver.	80.447	63.955	16.493 ***	(1.064)	25.79
	Cropping calendar	79.058	63.596	15.463 ***	(0.844)	24.31
	Input mix	80.807	64.367	16.440 ***	(0.946)	25.54
	Soil and water conservation	79.267	63.487	15.780 ***	(0.789)	24.86

*** Significant at 1% level.

4. Conclusions and Policy Implications

This paper examined the drivers of adoption of different climate-smart agricultural (CSA) practices (changing cropping calendar, diversifying seed variety, changing input mix and soil and water conservation), and the impact of the adoption of these practices on farm net returns and farmers' exposure to production risk. The study utilized recent survey data from three cropping zones of Pakistan and employed a multinomial endogenous switching regression (MESR) model to account for selection bias. The empirical results revealed that access to current climate information tends to enhance the effective adoption of CSA practices. Other factors that were found to significantly drive adoption decisions among farmers include ownership of agricultural machinery, extension services, previous experience with climate-related shocks, and education of the household head.

The results further demonstrated that soil and water conservation as a CSA practice exerted the highest positive influence on farm net returns, followed by input mix, diversifying seed variety, and changing cropping calendar, respectively. The findings also revealed that all the CSA practices significantly reduced downside risk exposure and therefore reduced the probability of crop failure among farm households. The findings further showed heterogeneity in the impacts of the adoption of CSA practices among different cropping zones. While in the cotton zone, adoption of seed variety diversification resulted in the highest impact on farm net returns, the adoption of soil and water conservation measures yielded the greatest impact on farm net returns in the mixed cropping zone. This finding implies that the promotion of CSA practices for scaling-up purposes should consider the agroecology of the area.

Overall, the findings showed that CSA practices can help in reducing the adverse impacts of climate change on crop productivity and should, therefore, be promoted across the country. Another policy implication is that promoting and scaling up the adoption of CSA practices could serve as an ex-ante measure against crop failures, particularly in areas where formal insurance institutions are not effective or nonexistent. Furthermore, policies that enhance access to extension services and access to credit and education, as well as timely information on climate change, would facilitate the adoption of CSA practices and contribute to improving rural farm household welfare.

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Appendix A

Table A1. Impact of CSFP choices on risk exposure, second stage MESR estimation.

Variables	Non-Adaptation		Seed Variety Diver.		Cropping Calendar		Input Mix		Joint Adoption	
	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
Constant	0.03628	0.26823	0.29792	(0.25590)	0.19908	(0.42937)	0.19706	(0.31410)	0.02621	(0.24854)
Credit_const	−0.00323	0.00992	0.00530	(0.01140)	−0.01619	(0.03432)	−0.00376	(0.02376)	−0.01794	(0.01351)
Avg_Tem	0.00043	0.0090	−0.01018	(0.00862)	−0.00594	(0.01453)	−0.00538	(0.01017)	0.00209	(0.00841)
Avg_Rain	0.06378	0.19669	0.09471	(0.15378)	0.32194	(0.34441)	−0.00527	(0.25039)	−0.01252	(0.19403)
int_TxR	−0.00253	(0.00830	−0.00478	(0.00634)	−0.01321	(0.01406)	−0.00024	(0.01022)	0.00116	(0.00797)
Tem_anomaly	−0.14928	(0.09828)	0.01656	(0.05081)	0.13051	(0.15198)	−0.16041	(0.12002)	−0.15006	(0.13445)
Rain_anomaly	0.00168	(0.01073)	0.00247	(0.01164)	0.02728	(0.01827)	−0.02207	(0.01525)	−0.04345 **	(0.01811)
HH_age	−0.00010	(0.00009)	−0.00004	(0.00008)	0.00005	(0.00013)	−0.00011	(0.00011)	−0.00018	(0.00011)
Family size	−0.00002	(0.00045)	0.00016	(0.00045)	0.00001	(0.00067)	0.00009	(0.00058)	−0.00020	(0.00057)
Education	−0.00210 **	(0.00105)	−0.00049	(0.00054)	−0.00231 *	(0.00128)	−0.00100	(0.00086)	−0.00161 **	(0.00079)
Plot size	0.00115 **	(0.00052)	−0.00037	(0.00025)	−0.00094	(0.00087)	0.00031	(0.00053)	0.00002	(0.00045)
Animal	−0.00110	(0.00092)	0.00000	(0.00046)	0.00010	(0.00095)	−0.00002	(0.00058)	0.00001	(0.00062)
Machinary	−0.00106	(0.00460)	0.00153	(0.00206)	0.00198	(0.00573)	−0.00868 **	(0.00387)	−0.00678 **	(0.00277)
Ext_services	0.02283 *	(0.01340)	−0.00529	(0.00863)	−0.00166	(0.01410)	0.01553	(0.01243)	0.01423	(0.01311)
cc_shock	−0.00807	(0.00557)	0.00157	(0.00315)	0.00237	(0.01024)	0.00539	(0.00752)	0.00957 **	(0.00446)
Xcotton	−0.00419	(0.00697)	0.00680	(0.00739)	0.01028	(0.01513)	−0.00646	(0.00997)	−0.01344	(0.00977)
Xrice	0.00255	(0.00630)	0.00606	(0.00637)	0.00538	(0.01143)	−0.00010	(0.00804)	−0.01207	(0.00759)
Fertility	0.00096	(0.00256)	0.00302	(0.00353)	0.01051 *	(0.00628)	−0.00270	(0.00474)	−0.00272	(0.00373)
Erosion	−0.00024	(0.00421)	−0.00480	(0.00414)	−0.01328	(0.00927)	0.00939	(0.00650)	0.00485	(0.00571)
Plot_distance	−0.00251 **	(0.00126)	0.00061	(0.00086)	0.00133	(0.00166)	−0.00076	(0.00110)	−0.00297 ***	(0.00098)
_m1	0.00659	(0.01015)	0.00220	(0.00923)	0.01090	(0.01447)	−0.00335	(0.01067)	0.01360	(0.00941)
_m2	0.00896	(0.02426)	−0.00075	(0.00460)	−0.00991	(0.02010)	−0.00155	(0.01673)	0.03175 **	(0.01574)
_m3	0.02590	(0.04804)	−0.02589 *	(0.01572)	−0.00600	(0.00889)	0.04198 **	(0.01998)	0.05874 ***	(0.01993)
_m4	−0.00280	(0.03785)	−0.00984	(0.01522)	0.00072	(0.02034)	−0.00564	(0.00705)	−0.00568	(0.01738)
_m5	0.01021	(0.04610)	0.02607 *	(0.01411)	0.04839	(0.04580)	−0.04882 **	(0.02201)	−0.01214 *	(0.00695)

Note: The dependent variable is the skewness, i.e., third central moment of net returns function. Bootstrapped standard errors are in parenthesis. The reference region is a mix-cropping zone. *** Significant at 1% level, ** significant at 5% level and * significant at 10% level.

Table A2. Test on the validity of selection and potential endogenous variable instruments (Farm net returns).

Net_Returns	Coef.	St.Err.	t-Value	*p*-Value	[95% Confidence Interval]		Sig
cc_info	−0.071	5.291	−0.01	0.989	−10.477	10.336	
cc_perception	1.344	5.037	0.27	0.790	−8.563	11.252	
dis_Ext_off	−0.053	0.220	−0.24	0.810	−0.485	0.379	
Relativ_bank	−1.276	3.054	−0.42	0.676	−7.283	4.732	
Constant	48.969	2.097	23.36	0.000	44.845	53.092	***
Mean dependent var		48.442		SD dependent var		13.749	
R-squared		0.001		Number of obs		351.000	
F-test		0.073		Prob > F		0.990	
Akaike crit. (AIC)		2844.693		Bayesian crit. (BIC)		2863.997	

*** $p < 0.01$.

Table A3. Test on the validity of selection and potential endogenous variable instruments (Skewness).

Skewness	Coef.	St.Err.	t-Value	*p*-Value	[95% Confidence Interval]		Sig
cc_info	0.002	0.006	0.32	0.750	−0.010	0.014	
cc_perception	−0.003	0.006	−0.45	0.652	−0.014	0.009	
dis_Ext_off	0.000	0.000	0.00	0.997	−0.001	0.001	
Relativ_bank	0.001	0.004	0.25	0.799	−0.006	0.008	
Constant	−0.005	0.002	−1.86	0.064	−0.010	0.000	*
Mean dependent var		−0.005		SD dependent var		0.016	
R-squared		0.001		Number of obs		351.000	
F-test		0.084		Prob > F		0.987	
Akaike crit. (AIC)		−1884.099		Bayesian crit. (BIC)		−1864.795	

* $p < 0.1$.

Table A4. Parameter estimates of potential endogenous variable credit constraints.

Credit_Cons	Coef.	St.Err.	t-Value	p-Value	[95% Confidence	Interval]	Sig
Avg_Tem	0.385	0.523	0.74	0.462	−0.640	1.409	
Avg_Rain	21.289	9.227	2.31	0.021	3.205	39.374	**
int_TxR	−0.779	0.390	−2.00	0.046	−1.543	−0.015	**
tem_anomaly	−3.887	4.256	−0.91	0.361	−12.229	4.455	
rain_anomaly	−0.457	0.562	−0.81	0.416	−1.558	0.644	
HH_age	−0.003	0.006	−0.53	0.594	−0.015	0.009	
familysize	−0.015	0.039	−0.38	0.705	−0.090	0.061	
Education	−0.085	0.025	−3.45	0.001	−0.133	−0.037	***
plot_size	0.028	0.023	1.22	0.221	−0.017	0.074	
no_of_animal	−0.055	0.038	−1.46	0.144	−0.129	0.019	
Ext_services	−1.034	0.187	−5.53	0.000	−1.400	−0.668	***
Clay_soil	0.262	0.227	1.16	0.248	−0.182	0.707	
Sandy_soil	0.080	0.205	0.39	0.697	−0.322	0.482	
cc_shock	0.865	0.143	6.03	0.000	0.584	1.146	***
Xcotton	−0.884	0.448	−1.97	0.049	−1.763	−0.005	**
Xrice	−0.320	0.353	−0.91	0.366	−1.012	0.373	
Relativ_bank	−0.714	0.317	−2.25	0.024	−1.335	−0.093	**
Constant	−9.820	15.214	−0.65	0.519	−39.640	20.000	
Mean dependent var		0.282		SD dependent var		0.450	
Pseudo r-squared		0.440		Number of obs		748.000	
Chi-square		391.808		Prob > chi2		0.000	
Akaike crit. (AIC)		534.181		Bayesian crit. (BIC)		617.294	

*** $p < 0.01$, ** $p < 0.05$.

Table A5. Parameter estimates of potential endogenous variable extension services.

Ext_Services	Coef.	St. Err.	t-Value	p-Value	[95% Confidence	Interval]	Sig
CreditConstant	−1.046	0.195	−5.36	0.000	−1.429	−0.664	***
Avg_Tem	0.104	0.444	0.23	0.815	−0.767	0.974	
Avg_Rain	2.285	7.989	0.29	0.775	−13.373	17.944	
int_TxR	−0.049	0.339	−0.14	0.886	−0.713	0.616	
tem_anomaly	6.120	4.318	1.42	0.156	−2.343	14.583	
rain_anomaly	−0.627	0.588	−1.06	0.287	−1.780	0.526	
HH_age	0.005	0.005	0.99	0.324	−0.005	0.016	
familysize	−0.021	0.032	−0.67	0.505	−0.084	0.041	
Education	0.185	0.021	8.82	0.000	0.144	0.226	***
plot_size	−0.057	0.024	−2.40	0.016	−0.103	−0.010	**
no_of_animal	0.020	0.034	0.58	0.563	−0.047	0.086	
Clay_soil	0.133	0.177	0.75	0.452	−0.213	0.479	
Sandy_soil	−0.224	0.200	−1.12	0.264	−0.617	0.169	
cc_shock	−0.155	0.162	−0.96	0.339	−0.472	0.162	
Xcotton	−0.450	0.381	−1.18	0.238	−1.196	0.296	
Xrice	−0.397	0.316	−1.25	0.209	−1.016	0.223	
dis_Ext_off	−0.048	0.021	−2.29	0.022	−0.090	−0.007	**
Constant	−5.544	13.229	−0.42	0.675	−31.472	20.384	
Mean dependent var		0.386		SD dependent var		0.487	
Pseudo r-squared		0.347		Number of obs		748.000	
Chi-square		346.715		Prob > chi2		0.000	
Akaike crit. (AIC)		687.257		Bayesian crit. (BIC)		770.370	

*** $p < 0.01$, ** $p < 0.05$.

Robustness check

Table A6. Treatment effects of adoption on farm net returns and downside risk exposure: multivariate treatment effect regression.

Adaptation Strategies	Obs.	Adopters Mean	Non-Adopters Mean	ATT	St. Err.	%Age Change
Farm net returns						
Seed variety diver.	98	68.543	58.572	9.971 ***	1.593	17.02
Cropping calendar	106	69.019	58.572	10.447 ***	1.581	17.84
Input mix	84	69.559	58.572	10.987 ***	1.713	18.76
Soil and water conservation	113	69.940	58.572	11.368 ***	1.688	19.41
Skewness						
Seed variety diver.	98	0.002	−0.007	0.002 ***	(0.001)	−128.57
Cropping calendar	106	0.005	−0.007	0.005 ***	(0.001)	−171.43
Input mix	84	0.002	−0.007	0.003 ***	(0.001)	−128.57
Soil and water conservation	113	0.004	−0.007	0.005 ***	(0.001)	−157.14

*** Significant at 1% level.

Table A7. Summary statistics of key variables by agroecological zones.

Variables	Cotton Zone		Mix Zone		Rice Zone	
	Mean	SD	Mean	SD	Mean	SD
No adaptation	0.498	0.501	0.540	0.499	0.352	0.479
Seed varieties diver.	0.116	0.321	0.091	0.288	0.132	0.339
Cropping calendar	0.124	0.331	0.136	0.343	0.164	0.371
Input mix	0.133	0.340	0.106	0.308	0.156	0.364
SWC	0.129	0.336	0.128	0.335	0.196	0.398
Credit_const	0.498	0.501	0.283	0.451	0.080	0.272
Avg Tem	26.89	1.636	27.433	0.111	27.642	0.949
Avg Rain	1.027	0.779	0.411	0.023	0.519	0.375
Int TxR	26.345	19.386	11.286	0.602	13.996	9.851
Tem anomaly	0.182	0.003	0.224	0.018	0.242	0.028
Rain anomaly	−0.317	0.220	−0.289	0.143	−0.503	0.138
HH age	45.936	11.927	47.287	9.841	48.344	11.926
Family size	5.163	1.854	6.215	2.129	6.992	2.278
Education	4.575	4.124	4.826	3.180	10.14	2.995
Plot size	5.506	3.100	6.471	4.123	5.772	3.314
Herd size	3.609	2.191	4.566	2.602	3.920	2.138
Machinery	0.172	0.378	0.170	0.376	0.400	0.491
Ext services	0.219	0.414	0.268	0.444	0.668	0.472
cc shock	0.421	0.495	0.336	0.473	0.120	0.326
Plot distance	2.421	1.716	2.287	1.321	1.668	1.069
cc info	0.318	0.467	0.298	0.458	0.504	0.501
cc perception	0.309	0.463	0.260	0.440	0.500	0.501
Net returns	49.195	16.593	53.736	12.786	74.074	12.19
Total land holding	8.204	7.826	10.710	10.812	9.281	8.356
Income per capita/month †	6514.23		7716.71		8193.66	
No. of Observations	233		265		250	

† National poverty line for Pakistan is 3250 PKR/month [34], therefore on average farmers are living above poverty line.

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