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Research article

Climate change adaptation and its impacts on farm income and downside risk exposure

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ABSTRACT

Multiple previous reports have established that climate change disproportionately impacts smallholder farmers in developing countries. This study investigates the impact of climate change adaptation, defined by farmers' decisions to adopt the improved practices to mitigate or reduce the effects of climate change, on crop revenue and revenue risk exposure. We employ the control function approach in an endogenous switching regression framework to account for selection bias. Using the household survey data from Nepal, we find that climate change adaptation positively affects crop revenue and revenue risk reduction. Specifically, climate change adaptation leads to a 21.6% increase in farm revenue and a 6.4% reduction in downside risk exposure, which are robust to several specifications. Counterfactual analysis shows the considerable heterogeneities in the outcomes among adapters and non-adapters. In particular, adapting farm households realize substantial and distinguishable gains in revenues and declines in risk levels relative to their non-adapting peer households. Our findings imply that adapting to climate change can be an effective management practice to mitigate the risks associated with climate change and increase resilience.

1. Introduction

Climate change is a persistent global threat that is extremely important and highly complex. The causes and consequences of climate change are diverse and manifested with some interesting irony whereby low-income countries, which contribute the least to climate change, are the most vulnerable to its effects (Tol, 2009). Crops are highly sensitive to climatic variations, which can affect both yields as well as the variance associated with the yield (Ray et al., 2015). Moreover, smallholder farmers are particularly susceptible to climate change, potentially due to conventional farming practices, inadequate access and limited affordability of technological advancements, reliance on rain-fed agriculture, and increasing incidence of poverty (Mulwa et al., 2017). This vulnerability in agricultural production caused by climate change can lead to food insecurity and reduce farmers' real income (Cervantes-Godoy et al., 2013). Potentially harmful climate change events include significant shifts in weather patterns, high levels of greenhouse gas emissions, change in atmospheric CO2 concentrations, increased global temperature, deterioration of water quality, and extreme climatic events such as severe flooding, droughts, and rising sea levels (Hoegh-Guldberg et al., 2019; Kulp and Strauss, 2019). These events have increased in recent years and may have increasingly negative impacts on agricultural activities. Faced with these conditions, farmers are compelled to make essential adaptation responses (Tang and Hailu, 2020).

Agricultural systems are highly dynamic, with producers and consumers continuously responding to changes in crop and livestock yields, food prices, input prices, resource availability, and technological change (Adams et al., 1998). To maximize output, increase income, and meet the food demands of a rapidly growing population, a focus on adaptation strategies to manage the risks posed by climate change in agriculture is warranted. Accordingly, a substantial body of literature has emerged that investigates the complex interactions between climate change, agricultural systems, and human responses. Previous studies have indicated that agriculture might benefit from climate change in the future if suitable adaptations are implemented (Dixon et al., 2003; Tingem and Rivington, 2009). While many farmers have implemented adaptation strategies by adjusting their farm management practices, the intensity and adaptation measures vary considerably based on climatic, social, economic, and institutional factors (IPCC (Intergovernmental Panel on Climate Change), 2007; Below et al., 2012; Deressa et al., 2009). Multiple studies on adaptation to climate change in developing countries show variations in farmers' responses to climate change in terms of planning (either short term or long term), timing (whether reactive or anticipatory), privacy (if decisions are private or public), and in various other forms such as technical, institutional, behavioral, or educational choices (Smit and Skinner, 2002; Venkateswarlu and

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Shanker, 2009; Alam, 2015; Kabir et al., 2017; Ngigi et al., 2017; Cui and Xie, 2021). These climate change adaptation decisions have been attributed to age, information, experience, capital availability, and access to credit facilities and institutions (Deressa et al., 2011) and may translate to differentials in agricultural productivity (Diallo et al., 2020).

Similarly, experience gained from changes in climatic patterns has also led smallholder farmers to adapt based on their existing knowledge and technologies (Leclère et al., 2013). These insights are crucial for identifying adaptation approaches at the field level and understanding their implications concerning crop revenue and risk exposures. However, micro evidence on the impacts of climate change adaptation techniques on farm income and associated variances is scant.

Recent studies have assessed the impact of adaptation on farm productivity based on farmers' actual practices. A study by Di Falco et al. (2011) on Ethiopian farmers finds that downside risk exposure actually decreased for farmers who implemented adaptation practices, while households that did not adapt to climate change would have realized considerable gains if only they had implemented adaptation practices. Similarly, a survey among rice farmers in China conducted by Huang et al. (2015) indicates that adapting agriculture to climate change increases rice yields and reduces the overall magnitude of risk, especially downside risk, of rice yields. However, adequate documentation of the effects of adaptation measures on farm income and downside revenue risk exposure is lacking.

This study utilizes survey data on Nepal to expand the empirical evidence on farm income and the risk implications of adapting to climate change. Our analytical framework is formulated with careful attention to deal with important modeling challenges. Firstly, since adaptation decisions are voluntary, farmers may self-select into adapter or non-adapter groups. This self-selection can lead to biased (inconsistent) parameter estimates. Moreover, unobserved heterogeneities in the characteristics of farming households may affect both the adaptation decision process as well as outcomes of interest. The omission of an innate ability variable, for instance, among the adapters could overestimate or underestimate the actual effect of adaptation decisions on farm households' crop revenue and revenue risks.

In order to achieve a robust causal estimation of the impact of climate change adaptation on crop revenue, it is vital that the estimation address the endogeneity issue. We employ a control function (CF) approach in the endogenous switching regression framework (ESR) that permits substantial heterogeneity to address this potential self-selection and omitted variable bias. The ESR-CF is modeled as a two-stage framework, where the first stage is a probit estimation of the adaptation decision, which is later employed to estimate the crop revenue equation using the CF approach where the adaptation decision is the only endogenous element in the ESR model. Combined with instrumental variables estimation, this CF approach/model estimates all parameters under standard maintained assumptions (Murtazashvili and Wooldridge, 2016). In this analysis, the instruments for adaptation decisions include distance to road, distance to market, distance to the extension service center, and climate information. Since we control for several household and farm characteristics, it is plausible to think that these instruments have no direct effects on crop revenue, thus satisfying the exclusion restriction. The selected instruments used in this study have been validated in the extant literature as strong predictors of farm households' adaptation decisions, which theoretically fulfills the relevancy requirement (Suri, 2011; Mishra et al., 2018; Cawley et al., 2018; Adego et al., 2019; Di Falco et al., 2011). Moreover, test results provide suggestive evidence of self-selection on adaptation decisions, which further validates our empirical strategy and highlights the heterogeneous effects of adaptation. This is the first study to deal with self-selection bias using the control function approach in analyzing climate change adaptation to the best of our knowledge.

Quantifying the effectiveness of climate change adaptation measures is vital to evaluate existing efforts and formulate new adaptation measures to offset the potential adverse effects of climate change and ensure food security. This study supports the contention that climate change profoundly impacts agriculture and affects crop productivity, quality, and revenue. Further, our findings will provide strong motivations for community leaders and crop growers worldwide to take measures to mitigate the consequences of climate change.

2. Geographical context

Nepal is an agricultural country, with nearly 66 percent of the active population engaging in agriculture for their livelihood and contributing around 35 percent of its GDP (MOAD, 2015). Nepal has a great deal of variation in climatic conditions. It can be broadly divided into four ecological regions: Terai (60 m above sea level (masl)- 500 masl), the Mid Hill (500–2000 masl), the Upper Hill (2000–3000 masl), and the Mountain (3000–8848 masl). Terai is the hottest part of the country, where the maximum temperature can go above 40 °C, while the mountain region remains largely cool with persistent snow throughout the year (Shrestha and Aryal, 2011). The major crops grown are rice, maize, wheat, barley, millet, buckwheat, potato, and oilseeds representing more than 90% of the total grain production and cultivated area (Gumma et al., 2011). The crop production system dramatically varies with the climatic and ecological regions. Crops are mostly grown from the lowlands of the Terai/plains to the Upper Hills. Crops primarily grown in Terai are rice, maize, wheat, and oilseeds. Maize and rice-based cropping systems are predominant in the Mid Hills. Rice production generally takes place in the wetlands, while the dryland is devoted to maize and wheat cultivation. Potato, barley, and buckwheat-based cropping system are practiced in the Upper Hills. However, low temperatures and short growing seasons limit crop growth in the high mountains rendering year-round agriculture practically impossible.

3. Data collection

The data set used in this study comes from household surveys conducted between August to November 2015. Based on the agro-climatic zones and regional cropping system, the survey covered three agro-ecological regions in Nepal: tropical (Terai), subtropical (Mid-Hills), and warm temperate (Upper-Hills). We first identified the major crop-producing districts in each of the three agro-ecological regions. We selected two districts within each agro-ecological region based on agricultural production in 2014: Chitwan and Nawalparasi in the Tropical region, Lamjung and Dhading in the Mid-Hills, Nuwakot, and Myagdi in the Upper Hills. Within each district, we selected four village development committees (VDCs[1]) to examine climate change adaptation and its potential impacts on crop revenue. The selection procedure starts with identifying all VDCs with the highest proportion of households that relied on farming for their living. From the identified VDCs, only those VDCs that also faced weather shocks during any growing season in the last five years were selected. From the list of VDCs identified in phase two, four VDCs from each district were selected with guidance from the District Agricultural Development Office. Subsequently, thirty households from each VDCs were chosen randomly using a random number generator for the survey, with 240 ($4 \times 30 \times 2$) households from each agro-ecological region. Our target population was smallholder farmers. This approach allows us to select the farming families that could have experienced weather shocks during their farming operations and resemble the average farming household in Nepal. Overall, the sample is a cross-section of 720 randomly selected households (240 households $\times$ 3 agro-ecological regions). After additional data cleaning protocols, the final sample size is reduced to 713 households.

The survey instruments used in the household survey were structured and pretested questionnaires. The survey collects comprehensive

[1] VDCs were the smallest administrative unit of Nepal at the time of survey.

information about household demographic characteristics, farm activities, crop production details, input use, yield, and revenue, climate change perception, information, and adaptation. For the primary outcomes of this study, we asked if a household employs any climate change adaptation measures. In the sample, 416 out of 713 households had adopted some adaptation measures when they were surveyed.

4. The two-stage household climate adaptation decision

A household's decision to adapt to climate change and the impact of adaptation decision on crop revenue is modeled in a two-step framework. The first stage consists of modeling the climate change adaptation decision. The household decision of whether to practice adaptation measures is considered under the random utility framework. The theoretical assumption posits that a farm household decides whether to adapt to climate change by taking into account the net benefit derived from adaptation and maximizing the expected utility.

Let D_i denote the binary adaptation indicator,[2] which takes on a value of 1 for a household i that adopts at least one farm management practice to mitigate the risks associated with climate change and 0 otherwise. A farm household i decides on whether to implement an adaptation strategy based on the expected net benefit and costs of adaptation (C_i. Assume U_{i0} and U_{i1} are expected utility derived from deciding to adapt and not to adapt, respectively. A farm household i selects into adaptation decision if the net utility U_i^* $\left(U_i^* = U_{i1} - U_{i0} - C_i\right)$ from doing so is positive. The net utility can be represented by a latent continuous variable, which is unknown to the researcher, but can be specified as a function of a vector of observable variables, z_i, and unobservables, ω_i as:

$$U_i^* = z_i\gamma + \omega_i, D_i = 1\left[U_i^* > 0\right] \qquad i = 1, 2, \ldots, N \tag{1}$$

where γ is a vector of coefficients, $1\,[.]$ is an indicator function which equals 1 if the statement inside the bracket is true and 0 otherwise, ω_i independently follows $N(0,1)$, and $i = 1, 2, \ldots, N$ are a number of households.

In the second stage, we model implementing climate change adaptation practices on crop revenue and downside revenue risk exposure. Let y_i be the crop revenues,[3] which is a linear function of exogenous farm and household characteristics X_i and the adaptation decision, D_i. In particular, y_i is assumed to be generated as

$$y_i = X_i\beta + \alpha D_i + \epsilon_i \tag{2}$$

where β represents a vector of parameters to be estimated, α is the coefficient associated with the binary indicator of adaptation D_i, and ϵ_i is an unobserved component.

4.1. Self-selection issue

The most common way to examine the impact of adaptation to climate change on crop revenue would be to estimate Eq. (2) by ordinary least squares (OLS). The OLS estimates, however, are not consistent because selection into adaptation decision is likely not random; instead the decision is voluntary and based on their self-selection. Selection into treatment determines the adaptation status, D_i. Nonrandom selection occurs if the unobserved component ϵ_i is correlated with an indicator of adaptation (i.e., $corr\left(D_i, \epsilon_i\right) \neq 0$) causing potential endogeneity (Imbens and Wooldridge, 2009). This implies that ϵ_i is either correlated with the regressors determining adaptation decision or correlated with an unobservable term in the selection equation, ω_i.

Individuals differ with respect to several observed and unobserved characteristics. Subsequently, there are two types of nonrandom selection: the selection on observables and unobservables. Selection on the unobservable may occur because farmers who choose to adapt to climate change may share common unobserved characteristics, such as innate managerial skill, technical abilities, individual preferences, and social networks, which could correlate with the outcome variables. For instance, if the most talented and determined farmers decide to adapt, but the model fails to account for such innate skills and farmers' motivation, estimates will be biased. On the other hand, adapting and non-adapting households may have systematically different observed characteristics that influence selection on the observables. Such features affect the cost of adaptation and/or expected return, leading to heterogeneous adaptation behaviors and the inaccurate effect of adaptation on crop revenue. Under homogeneous treatment effects, selection bias occurs if D_i is correlated with ω_i whereas the selection Eq. (1) becomes more severe in the presence of heterogeneous treatment effects when the correlation between ω_i and D_i may arise through ϵ_i or the idiosyncratic gains from adaptation (Blundell and Dias, 2009).

4.2. Endogenous switching regression

Several approaches have been used to solve this problem: (a) selection models (Heckman and Robb, 1986; Powell, 1994), (b) instrumental variable models (Heckman and Vytlacil, 2005; Heckman et al., 2006), and (c) matching methods[4] (Heckman and Navarro-Lozano, 2004). To account for the endogeneity problem discussed above, we utilize the endogenous switching regression (ESR) model studied by Heckman (1976), where the coefficient on a binary endogenous variable is allowed to differ across units in both observed and unobserved ways. The ESR can be estimated with the two-step method using the control function (CF) or simultaneously via full information maximum likelihood (ESR-FIML). The ESR-FIML developed by Lokshin and Sajaia (2004) has increasingly been used in climate change adaptation studies (Di Falco and Veronesi, 2014; Huang et al., 2015; Ojo and Baiyegunhi, 2020). Wooldridge (2010) notes that the maximum likelihood (ML) method produces the most efficient estimators and asymptotically correct standard error estimates under the appropriate assumption. However, ML estimators are likely to be vulnerable to misspecification (Greene, 2003, p.421). Under certain circumstances, such as dealing with small sample size, the ML estimation can be computationally complicated and costly to implement, limiting its use (Nguimkeu et al., 2019). For instance, correlations between the selection Eq. (1) and the outcomes Eq. (2) errors might not be efficiently estimated, resulting in multiple local maxima or, at times, leading to non-convergence problems. Further, the ML jointly estimated parameters are computationally taxing as they would require full specification of joint distribution and high

[2] We code the *adaptation* as a binary variable which takes a value 1 if a farm household implemented at least one adaptation measure a year prior to the survey year, and otherwise zero. In our sample, in many cases, households implemented more than one adaptation and it is not possible to disentangle the effect of individual adaptation measure on the outcome of interest. If a farm household implemented any coping measures they are likely to follow other strategies in response to changing climatic and weather conditions. In additional, considering the sample size, we did not fit a binary probit regression models separately for each of adaptation strategies (or multivariate probit models).

[3] Crop revenue is the sum the net crop revenues (gross revenue-variable cost of productions) per hectare of cropland from all crops in a cropping year prior to the survey year.

[4] Matching is also used, which is a form of non-parametric least-squares that assume that all relevant unobservables are accurately proxied by observable. The widely used matching methods are propensity score matching and inverse probability-weighted with regression adjustment (Cattaneo et al., 2013; Tilahun et al., 2016). Rosenbaum and Rubin (1983) defined the propensity score as the conditional probability of assignment to a treatment given a vector of covariates. Based entirely on the observed characteristics, the matching approaches balance the observed distribution of covariates across adopting and non-adopting households. However, these approaches do not account for unobservable characteristics, thus leading to misspecification and inconsistent estimators (Andam et al., 2008). Further, results of propensity score matching may be biased due to propensity score model misspecification.

dimensional integration (Peel, 2014; Murtazashvili and Wooldridge, 2016).

In contrast, the two-step method always results in convergence. A CF approach, combined with instrumental variables, produces consistent estimation in the presence of endogenous regressors under standard identification assumptions (Wooldridge, 2015). It takes into account the non-linear interaction between an endogenous regressor and the error terms (Adepoju and Oni, 2012). Besides, unlike the ESR-FIML, the ESR-CF approach provides a direct marginal effect of endogenous binary treatment on outcome variables. The ESR-CF will provide consistent estimates in the presence of unobserved heterogeneity between adapters and non-adapters (Murtazashvili and Wooldridge, 2016). Considering these issues, we employ the CF in the ESR model studied by Murtazashvili and Wooldridge (2016).[5]

Consider the following ESR model

$$y_i = \left(1 - D_i\right) X_i\beta_0 + D_i X_i \beta_1 + \left(1 - D_i\right) \epsilon_{i0} + D_i \epsilon_{i1} \tag{3}$$

where D_i is the endogenous switching indicator for individual i, X_i is a vector of exogenous covariates, with the first element being unity, and ϵ_{i0} and ϵ_{i1} are unobservables. It can be derived by simple substitution from a counterfactual framework:

$$y_i = \left(1 - D_i\right) y_i^0 + D_i y_i^1 \tag{4}$$

$$y_i^0 = X_i\beta_0 + \epsilon_{i0} \tag{5}$$

$$y_i^1 = X_i\beta_1 + \epsilon_{i1} \tag{6}$$

where y_i^0 and y_i^1 are the counterfactual outcomes, and a binary variable D_i can be correlated with $(\epsilon_{i0}, \epsilon_{i1}$. To estimate the ESR model, Eq. (4) can be written as

$$y_i = X_i\beta_0 + D_i X_i \gamma + \epsilon_{i0} + D_i \vartheta_{i1} \tag{7}$$

were $\vartheta_{i1} = \epsilon_{i1} - \epsilon_{i0}$ and $\gamma = \beta_1 - \beta_0$. Without the presence of $D_i\vartheta_{i1}$, we could estimate Eq. (7) by standard instrumental variable estimators. In this case, the standard instrumental variable estimators will be inconsistent. The problem with applying the instrumental variable method in the above equation is that the term $D_i\vartheta_{i1}$ is assumed to be correlated with explanatory variables X even under strong independence assumption because of the endogeneity of D_i (Murtazashvili and Wooldridge, 2016). However, we can identify Eq. (7) using a CF for D_i. Let z_{1i} be an instrumental variable (excluded exogenous variable from X_i for D_i, so that $z_i = f\left(X_i, z_{1i}\right)$, a vector of exogenous variables. We can therefore write

$$D_i = 1\left[z_i\pi + \omega_i > 0\right] \tag{8}$$

where π is a vector of coefficients for excluded exogenous variables.

Now, we make the following two assumptions

1. $(\vartheta_{i1}, \omega_i)$ is independent of z_i
2. $\omega_i \sim N(0, 1)$.

Under these assumptions, the generalized error function, which has a mean zero conditional on D_i, z, is given by:

$$E\left(\omega_i | D_i, z_i\right) = g\left(D_i, z_i\pi\right) = D_i\lambda\left(z_i\pi\right) - \left(1 - D_i\right)\lambda\left(-z_i\pi\right), \tag{9}$$

where $\lambda(.) = \phi(.)/\Phi(.)$ is inverse Mill's ratio (IMR), and $\phi(.)$ and $\Phi(.)$ are the standard normal density and cumulative distribution functions, respectively (Wooldridge, 2015).

Then, the estimating resulting equation becomes

$$E\left(y_i | D_i, z_i\right) = X_i\beta_0 + D_i X_i \gamma + E\left(\left(\epsilon_{i0} + D_i\vartheta_{i1}\right)/D_i, z_i\right). \tag{10}$$

Generally, $E\left(\epsilon_{i0} + D_i\vartheta_{i1}/z_i, D_i\right)$ depends on the joint distribution of $\left(\epsilon_{i0} + D_i\vartheta_{i1}, D_i\right)$ given z_i.

Again, from the linearity assumption, $E\left(\epsilon_{i0}|\omega_i\right) = \rho_0\omega_i$, and $E\left(\vartheta_{i1}|\omega_i\right) = \rho_1\omega_i$, where $\rho_0 = E\left(\omega_i, \epsilon_{i0}\right)/E\left(\omega_i{}^2\right)$, and $\rho_1 = E\left(\omega_i, \epsilon_{i1}\right)/E\left(\omega_i{}^2\right)$ are the population regression coefficients (Wooldridge, 2010). These would then result in the following:

$$E\left(\epsilon_{i0} + D_i\vartheta_{i1} | D_i, z_i\right) = \rho_0\omega_i + D_i\rho_1\omega_i = \left(\rho_0 + D_i\rho_1\right)\omega_i. \tag{11}$$

Using the Eqs. (9) and (11)

$$E\left(\epsilon_{i0} + D_i\vartheta_{i1} | D_i, z_i\right) = \left(\rho_0 + D_i\rho_1\right)\left\{D_i\lambda\left(z_i\pi\right) - \left(1 - D_i\right)\lambda\left(-z_i\pi\right)\right\}. \tag{12}$$

Given all of the above formulations and derivations, the resulting equation then becomes,

$$E\left(y_i | D_i, z_i\right) = X_i\beta_0 + D_i X\gamma + \left(\rho_0 + D_i\rho_1\right)\left\{D_i\lambda\left(z_i\pi\right) - \left(1 - D_i\right)\lambda\left(-z_i\pi\right)\right\}. \tag{13}$$

The parameters in generalized error function and IMR are estimated from a first-stage probit. In order to achieve identification, we should satisfy the exclusion restriction whereby we need at least one excluded exogenous variable (z_{1i} in the probit model for D_i that is not included in the outcome equation). We also require evidence of $\pi \neq 0$ for the instrument to be valid and need to impose a rank condition to ensure consistency.

4.3. Control function approach

Under the given assumptions, the following two-step procedure gives consistent parameter estimates. The first step involves the estimation of the probit model of D_i on $z_i\left(z_i = X_i, z_{1i}\right)$ as

$$P(D_i = 1 | z_i) = \Phi(z_{1i}\pi_1 + X_i\pi_2) \tag{14}$$

where π_1 and π_2 are coefficients. In order to achieve identification, we impose the usual exclusion restriction. The excluded exogenous variable(s) should affect the adaptation decision but not directly affect the yield. In other words, the effect of the instrumental variables on the outcome should come only through the adaptation.

Accordingly, the main challenge in this approach is identifying suitable instruments. We exclude from the crop revenue equation the following four exogenous covariates — climate information, distance to road, distance to market, and distance to nearest extension service center-from the outcome equation to exploit them as instruments for adaptation decision. These instruments have been used in several past studies, such as distance to market (Suri, 2011; Mishra et al., 2018), distance to the nearest extension center (Cawley et al., 2018; Issahaku and Abdulai, 2020), distance to the road (Dhakal and Escalante, 2022), distance to the market (Suri, 2011; Adego et al., 2019), and climate information (Di Falco et al., 2011; Khanal et al., 2018). The excluded instruments, z_i have to be strongly correlated with the endogenous adaptation status, D_i and uncorrelated with the unobservable error, ω_i. The exclusion restrictions ($E\left[z'\omega\right] = 0$ cannot be directly tested, but an identification test is feasible as there are more excluded instruments than an endogenous regressor. The condition $E\left[z_i' X_i\right] \neq 0$ determines the strength of identification. We maintain that the instruments have no direct effects on crop revenue once we control the adaptation decision. Since we control for several household and farm characteristics, it is plausible to think that these instruments satisfy the exogeneity and relevancy requirement and can be considered valid instruments for adaptation decisions.

In the second step, generalized residuals are obtained as

$$\hat{r}_i = D_i\lambda\left(z_i\hat{\pi}\right) - \left(1 - D_i\right)\lambda\left(-z_i\hat{\pi}\right). \tag{15}$$

Subsequently, our preferred estimating equation would be

$$y_i = X_i\beta_0 + D_i X_i\gamma + \rho_0\hat{r}_i + \rho_1 D_i\hat{r}_i + \epsilon_i \tag{16}$$

which is estimated by two-stage least squares using instrumental variables $(z_i, D_i z_i, \hat{r}_i, D_i\hat{r}_i)$ and where $\beta_0\ \gamma\ \rho_0, \rho_1$ are the parameters. We use the Huber/White sandwich estimator for the robust heteroskedasticity standard errors and standard errors clustered at the village level.

In the final step, Eq. (16) is estimated separately when $D_i = 1$ and $D_i = 0$ to get different estimations for adapters $(y_i{}^{(1)})$ and non-adapters

[5] Unlike Murtazashvili and Wooldridge (2016), we assume all covariates (except a binary *adaptation* variable) in the ESR model to be exogenous.

($y_i^{(0)}$), where IMR are $\lambda\left(z_i\hat{\pi}\right)$ and $\lambda\left(-z_i\hat{\pi}\right)$, respectively. In doing so, the estimating equation would be

$$y_i^{(1)} = X_i\beta_1 + (\rho_0 + \rho_1)\hat{r}_i + \epsilon_i \tag{17}$$

$$y_i^{(0)} = X_i\beta_0 + \rho_0\hat{r}_i + \epsilon_i. \tag{18}$$

4.4. Counter-factual analysis

Since this analysis examines the effect of climate change adaptation decisions on crop revenue and downside revenue risk exposure, it is then designed to estimate the treatment effect. The difficulty of observing the same household in both adapting and non-adapting conditions leads to various population-level treatment effects used in applied economics (Heckman and Vytlacil, 2005). The three most used treatment parameters to explore the impact of adaptation in the program evaluation literature are the average treatment effect (ATE), average treatment effect on treated (ATT), and average treatment effect on untreated (ATU). The ATE measure would be the average outcome if individuals were randomly assigned to treatment, and ATT measures the average effects on individuals specifically assigned to treatment. ATT, then, is the appropriate parameter to identify the impact of adaptation on adapting households. If, however, the interest focus is on the impact of adaptation on households of a certain type as if they were randomly selected, then ATE is the parameter of interest to recover. The ATE, ATT, and ATU measures are defined using conventions introduced by Wooldridge (2015), as follows:

$$ATE = E\left(y_i^{(1)} - y_i^{(0)}\right). \tag{19}$$

From Eqs. (17) and (18) ATE can be written as

$$ATE = X\beta_1 + \left(\rho_0 + \rho_1\right)\hat{r}_i - X\beta_0 + \rho_0\hat{r}_i = (\beta_1 - \beta_0)X + \rho_1\hat{r}_i. \tag{20}$$

The $y_i^{(1)}$ and $y_i^{(0)}$ are not directly observed, but $\hat{y}_i^{(1)}$ and $\hat{y}_i^{(0)}$ can be estimated from the above equation, as follows:

$$\widehat{ATE} = N^{-1}\sum_{i=1}^{N}[\hat{y}_i^{(1)} - \hat{y}_i^{(0)}]. \tag{21}$$

The effect of adoption on the adopting farm household (*i.e.*, ATT)) is given by

$$ATT = E\left(y_i^{(1)} - y_i^{(0)}|D_i = 1\right). \tag{22}$$

The ATT can thus be estimated as

$$\widehat{ATT} = N^{-1}\sum_{i=1}^{N} y_i(D_i = 1)[\hat{y}_i^{(1)} - \hat{y}_i^{(0)}]. \tag{23}$$

On the other hand, the effect of adaptation on the non-adapting households (ATU) is given by

$$ATU = E\left(y_i^{(1)} - y_i^{(0)}|D_i = 0\right). \tag{24}$$

The ATU is estimated as

$$\widehat{ATU} = N^{-1}\sum_{i=1}^{N} y_i(D_i = 0)[\hat{y}_i^{(1)} - \hat{y}_i^{(0)}]. \tag{25}$$

5. Results

We first report summary statistics of variables used in our analysis. We then estimate the Eq. (16) for the full sample and Eq. (17) and Eq. (18) for adapting and non-adapting households, respectively, to examine the extent to which the estimated effect is heterogeneous across adaptation status.

5.1. Summary statistics

Table 1 reports summary statistics and statistical significance tests on equality of means and proportions for continuous and dummy variables, respectively. Overall, 58 percent of farmers in our sample reported using at least one adaptive measure against climate change. More than two-thirds of adapting households have implemented multiple adaptation practices in response to climate change. Detailed farm household's adaptation strategies are provided in Appendix A.

Results presented in Column 4 in Table 1 clearly show that households that adapt to climate change are different from those that do not. In our sample, adapting households, on average, cultivated 0.24 more hectares, were 11.8 percent more likely to have access to irrigation, and usually had a household head 1.8 years younger than their non-adapter peers. Adapting households were also 20.7 percent more likely to have an educated household head and 15.3 percent more likely to access credit services. Further, they were also 21.1 percent more likely to have attended a training or meeting on climate change. The average adapting household in our sample earned 9138.7 Nepalese Rupees more in crop revenues each year than non-adapters. Although this difference in crop revenue is statistically significant at the five percent level, it does not account for selection bias due to observed and unobserved heterogeneities among the two types of households. These attributes have to be considered while designing adaptation interventions. Appendix B presents the distribution of crop revenue by adaptation status. As the plots indicate, when the distribution shifted to the right, adapters have higher crop revenue than non-adapters.

5.2. Are instruments valid?

To account for the potential endogeneity of adaptation status arising from self-selection, we instrumented the adaptation decision with four instrumental variables (IVs); climate information and distance to road, market, and nearest extension center. The validity of the IVs is a major challenge in the identification strategy of our model as it is not a testable hypothesis. In order for the IVs to be valid instruments, they have to satisfy two conditions: (1) IVs should affect the probability of adaptation decision, which is a nontrivial function of instruments; and (2) they should not have a direct effect on crop revenue, but instead affect outcomes only through the possibility of adaptation conditional on covariates. Three of the four variables are distance measures generally assumed to be exogenous to the decision to adapt (see Card, 2001; Carneiro et al., 2017; for instance). Each distance variable is coded in terms of self-reported time instead of the physical distance. This is because farm households can easily measure how long it takes to get to their destinations. We argue that location of residence is exogenous after we account for a detailed set of individual and farm characteristics, namely age, education status, dummies for agro-ecological regions, land area, and indicator for irrigated land.

Appendix C provides the results of the validity tests of the instruments. We ran probit regression model where the dependent variable takes a value of 1 if a farm household implemented at least one adaptation strategy; otherwise, zero. The results establish the strength of the IVs as determinants of farmers' adaptation decisions. All four instruments were jointly significant at the 1 percent level. The F-statistic value in the first stage regression is 93.96 (p-value<0.0001), which satisfies the theoretical relevancy requirement for instrument validity. Appendix C also reports the *p*-value results for testing the null hypothesis that IVs affect crop revenue. Results of a joint test on all IV coefficients indicate that IVs determine the crop revenue directly. Another issue with IVs is their strength. We empirically tested the weak instrumental variables issue and rejected the null hypothesis that our IVs are weak (Stock and Yogo, 2005).[6] Moreover, we argue that our IVs

[6] Assuming tolerable bias rate of 5%, for four excluded IVs to instrument for a single endogenous variable the critical value of the Cragg-Donald Wald statistic (F-statistic) is 13.91.

Table 1
Descriptive statistics of variables.

Variable name	Full Sample (1)	Adapters (2)	Non-adapters (3)	Difference (4)
Male	0.561	0.500	0.646	−0.146***
	(0.020)	(0.018)	(0.031)	
Age (years)	47.233	46.478	48.290	−1.811**
	(0.546)	(1.171)	(0.547)	
Household size (log)	1.778	1.797	1.750	0.046
	(0.023)	(0.032)	(0.031)	
Cultivated area (ha)	0.420	0.523	0.276	0.247***
	(0.035)	(0.058)	(0.022)	
Educated	0.666	0.752	0.545	0.207***
	(0.037)	(0.027)	(0.077)	
Access to credit	0.487	0.550	0.397	0.153***
	(0.022)	(0.031)	(0.049)	
Irrigated land	0.504	0.553	0.434	0.118***
	(0.036)	(0.055)	(0.020)	
Location-Terai[a]	0.337	0.313	0.370	−0.057
	(0.335)	(0.322)	(0.350)	
Location-Mid-hill[a]	0.328	0.334	0.320	0.014
	(0.334)	(0.343)	(0.321)	
Training/meeting attended	0.494	0.582	0.370	0.211***
	(0.041)	(0.081)	(0.019)	
Annual temperature (°C)	28.850	29.200	28.370	0.830
	(0.235)	(0.256)	(0.186)	
Annual precipitation (mm)	2377.819	2302.387	2483.475	−181.087**
	(61.912)	(116.324)	(42.996)	
Total assets ('00,000 NPR)	25.522	27.077	24.411	2.666
	(4.857)	(5.772)	(4.138)	
Distance to the nearest market (minutes)	19.972	14.433	27.731	−13.297***
	(0.572)	(0.217)	(1.015)	
Distance to the nearest road (minutes)	29.312	15.824	38.942	−23.117***
	(1.705)	(2.121)	(2.393)	
Climate information	0.456	0.582	0.279	0.302***
	(0.015)	(0.028)	(0.017)	
Distance to the nearest extension center (minutes)	26.067	19.320	35.519	−16.198***
	(1.696)	(1.029)	(3.222)	
Crop revenue (log NPR)	10.898	10.979	10.785	0.194***
	(0.048)	(0.056)	(0.065)	
Adaptation	0.583			
	(0.022)			
N	713	416	297	

Notes: Robust standard errors clustered at the village level are in parentheses. *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level.
NPR: Nepalese Rupee, Exchange rate: 1 US $ = Nepalese Rupees 106 at the time of survey (https://www.nrb.org.np/).
[a]Of the three regions, Upper Hill is the excluded category in the geographical location dummy variable.

satisfy the exclusion restriction criteria after controlling for covariates. In addition, we checked the validity of these instruments by performing a simple falsification test based on the premise that valid instruments affect the adaptation decision but will not affect the crop revenue per hectare among farm households that did not adapt (Di Falco et al., 2011). Our instruments are statistically significant determinants of climate change adaptation decision (Chi-square statistics = 299.72 and p-value = <0.001) but not of crop revenue and downside revenue risk exposure among non-adapting households (F-statistics = 24.79 and p-value = <0.001).

5.3. Drivers of adaptation decision

A probit regression model is estimated to quantify the impacts of various explanatory variables affecting a household's decision to adapt. Column 2 of Table 2 presents the probit model estimates from our probit model with adaptation decision as a dependent variable, which helps explain why some households implement adaptation measure(s) and others do not. Column 3 provides the marginal effects of the probit estimates the impacts of unit changes in explanatory variables on the dependent variable.

All three distance-based instrumental variables have significant and negative effects on the probability of adapting. Our findings indicate that farmers with easy access to roads, extension centers, and markets are more likely to implement climate change adaptation. Results suggest that access to resources and government technical services can lessen implementation constraints and are more likely to adapt to climate change. Similarly, having access to irrigation services, participation in training or meetings related to climate change, and the annual temperature was also associated with increased adaptation rates. Female farmers tend to be more inclined to implement adaptation measures. These findings are consistent with previous findings of earlier studies.

Structural and demographic factors also influence the adaptation decision; having an extra hectare of land under cultivation made farmers 11.3 percent more likely to adapt, while having 100,000 Nepalese Rupees more in assets also increased the probability of adaptation by 5 percent. Both of these estimates are statistically significant at the 5 percent level. Bryan et al. (2009), for instance, find that wealth is a key determinant in farmers' decision to adapt and that adaptation increased with improved access to extension, credit, and climate information in Ethiopia. This relationship is likely attributed to the fact that affluent households have the ability to absorb shocks and are more resilient. This result supports evidence that poor farm households may be more vulnerable to adverse effects of climate change (Wang et al., 2014; Huang et al., 2015). Obayelu et al. (2014) and Trinh et al. (2018) establish that high farm incomes, female farmers, farmers'

Table 2
Estimation of farmer's adaptation decision and its impact on crop revenue.

Variable name	Adaptation (1/0) Probit (1)	dy/dx[a] (2)	Crop revenue (NPR) OLS (3)	Crop revenue (NPR) CF (4)
Male	−0.547***	−0.212***	0.223***	0.221***
	(0.131)	(0.051)	(0.037)	(0.036)
Age (years)	0.020	0.008	0.012*	0.013*
	(0.018)	(0.007)	(0.007)	(0.007)
Household size (log)	0.023	0.009	0.028	0.027
	(0.157)	(0.061)	(0.043)	(0.043)
Cultivated area (ha)	0.292***	0.113***	0.036***	0.039***
	(0.050)	(0.019)	(0.014)	(0.014)
Educated	0.444***	0.172***	0.156***	0.153***
	(0.139)	(0.054)	(0.041)	(0.041)
Access to credit	0.213	0.083	0.108***	0.101***
	(0.131)	(0.051)	(0.036)	(0.036)
Irrigated land	0.229*	0.089*	0.104***	0.100
	(0.131)	(0.051)	(0.036)	(0.036)
Location-Terai[b]	−0.935***	−0.363***	0.017	0.005
	(0.172)	(0.067)	(0.045)	(0.045)
Location-Mid-hill[b]	−0.424***	−0.164***	−0.103**	−0.114***
	(0.164)	(0.063)	(0.044)	(0.044)
Training/meeting attended	0.290**	0.113**	0.099***	0.096***
	(0.133)	(0.052)	(0.037)	(0.037)
Annual temperature (°C)	0.358***	0.139***	0.111***	0.108***
	(0.135)	(0.052)	(0.039)	(0.039)
Annual precipitation (mm)	−0.000	−0.000	−0.000*	−0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Total assets ('00,000 NPR)	0.014***	0.005***	0.001**	0.002***
	(0.003)	(0.001)	(0.001)	(0.001)
Distance to the nearest market (minutes)	−0.027***	−0.010***		
	(0.006)	(0.002)		
Distance to the nearest road (minutes)	−0.365**	−0.142**		
	(0.152)	(0.059)		
Climate information	0.672***	0.261***		
	(0.136)	(0.053)		
Distance to the nearest extension center (minutes)	−0.053***	−0.021***		
	(0.006)	(0.002)		
Adaptation			0.091**	0.216***
			(0.039)	(0.065)
Generalized residual				−0.114***
				(0.044)
Constant	0.307		10.039***	9.958***
	(0.543)		(0.179)	(0.183)
R-squared			0.214	0.221

Notes: CF represents the control function approach. Robust standard errors clustered at the village level are in parentheses. *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level.
[a]dy/dx, Marginal effect, which is computed at the mean value of the X variables. NPR represents Nepalese Rupee, exchange rate: 1 US $ = Nepalese Rupees 106 at the time of survey (https://www.nrb.org.np/).
[b]Of the three regions, Upper Hill is the excluded category in the geographical location dummy variable.

accumulation of information on climate change, and greater access to credit services and extension services are key determinants in farmers' adaptation decisions. In addition, our finding on the significance of the household head's education status is consistent with previous findings (Deressa et al., 2011; Di Falco and Veronesi, 2014). However, factors affecting adaptation measures are often context and location-specific, thus requiring caution in interpreting results. In this regard, Toth et al. (2017) acknowledged that defined factors determining adaptation measures are not always apparent.

5.4. Impact on crop revenue

Column 4 in Table 2 presents the results of an ordinary least squares (OLS) estimation of crop revenues with an indicator variable for the adaptation and no switching decision. Column 5 in Table 2 presents coefficient estimates from the ESR-CF described in the previous section, again with crop revenues (in Nepalese Rupees) as the dependent variable. Our main finding is that adaptation decision against climate change results in higher crop revenues for farmers. Based on our OLS specification, we find that households that adapt to climate change earn 9.1 percent more in crop revenues compared to non-adapting households. This effect increases to 21.6 percent when using our CF specification. This disparity between the OLS and CF estimates is due to the fact that the latter accounts for unobserved heterogeneities. In contrast, the OLS specification does not accommodate such differences in unobservable characteristics, thus leading to biased estimates.

An important consideration in this analysis is the coefficient estimate on generalized residuals obtained in the CF model. Here, the coefficient is negative and statistically significant, implying selection bias due to systematic differences in observables and unobservables factors between adapters and non-adapters. Results also show that the downside bias due to self-selection is substantial, resulting in suboptimal policy decisions if ignored. This means we are justified in using the CF model that has shown the capability of attributing a greater portion of the effect of adaptation on crop revenue.

The control variables in our models are farm and household characteristics (age, education, family size, land area, and access to credit), climatic variables (annual temperature and precipitation), and place of residence. We also interact generalized residual with all included exogenous variables in the model.[7] It is useful to estimate such a rich model for two reasons; (1) the model is fairly flexible, and (2) by allowing the impact of generalized residual (which is an instrument for adaptation status) to vary with individual and farm characteristics, additional variation in the instrument will be allowed.

Most of our coefficient estimates from our two specifications have the same (expected?) signs and statistical significance. Key determinants of crop revenues are the same as those driving adaptations. We find that gender, education, access to credit services, information and extension services, and area under cultivation are the most important drivers of crop revenues. The only variable statistically significant in the OLS regression but not in the CF regression is irrigation. We hypothesize this might be due to selection bias in the OLS estimates.

Appendix D shows the coefficient estimates of crop revenues among adapting and non-adapting households from the ESR-CF. We find differential effects of covariates on crop revenue across adapters and non-adapters. For non-adapting households, age, education status, and annual temperature are important factors affecting crop revenue, while coefficient estimates of these variables are not statistically significant among adapters. On the other hand, crop revenues earned by adapters are affected by access to credit services, irrigation, and participation in training or meetings. Gender and the area under cultivation are significant factors affecting crop revenues for both adapters and non-adapters.

5.5. The skewness of crop revenues

An important aspect of crop production, especially for farmers in developing countries, is the downside risk associated with crop revenue. This analysis measures downside revenue risk exposure using the third moment of the revenue distribution function. An increase in crop revenue skewness indicates a reduction in downside risk (signifying decreases in the probability of crop failure and lower revenues). Column 2 in Table 3 reports the OLS coefficients results, using skewness of crop revenue as the dependent variable. The coefficient on the variable of interest, adaptation, is not significant, thus implying that adaptation does not affect the households' downside revenue risk exposure. However, this approach assumes that the adaptation decision is exogenously determined while it may be potentially endogenous due to sample selection. Hence, the OLS estimates may be inaccurate and inconsistent. Columns 3, 4, and 5 present the endogenous switching regression-control function (ESR-CF) model estimates, which account for sample selection in the skewness function. Our results from the full sample (Column 3 in Table 3) show that having an older and educated household head, more area under cultivation, higher levels of assets, greater access to credit services and irrigation facilities, and participation in training and meetings are associated with increases in the skewness of crop revenues. Our sample shows that using at least one adaptation strategy against climate change results in a 6.4 percent increase in skewness. Differences in skewness are essential to farmers as an increase in skewness indicates a reduction in downside risk and a decrease in the probability of crop failure (Di Falco and Chavas, 2009). Similarly, an increase in the skewness of revenue will protect farmers against the downside risk in income from farming.

We also use our CF specification to determine factors affecting skewness separately for adapters and non-adapters. The difference in the skewness estimates between these two household categories explains the presence of substantial heterogeneity. In the case of adapters, we find access to credit services and the area under cultivation as the most critical determinants of skewness. Having access to credit increases the skewness associated with crop revenues by 5.9 percent, while the effect of cultivating an extra hectare of land on skewness is an increment of 2.4 percent. Besides these, age and total assets owned are significant determinants of skewness for adapting households. On the other hand, among non-adapters, the most important factors affecting skewness in revenue are education status, access to irrigation services, and participation in climate change meetings.

5.6. Heterogeneity analysis

The ESR-CF model can be applied further to produce corrected predictions of counterfactual crop revenue and downside revenue risk exposure. It can be used to compare the expected crop revenue and downside revenue risk exposures of adapting and non-adapting households. Specifically, this extension can examine the crop revenue and expected downside revenue risk exposure in the counterfactual case when adapting households had not adapted and non-adapting households had they adapted. Table 4 reports the estimates for the average treatment effects (ATT and ATU) of adaptation on crop revenue and downside revenue risk exposure. Results indicate that adapting households have significantly higher crop revenues and experience lower levels of downside risk. Unlike simple differences in mean, these coefficients also account for selection bias due to systematic differences between adapters and non-adapters. On average, adapting households earn around 13 thousand Nepalese rupees more annually than they would have had they decided not to adapt. The annual difference in the average treatment effects between adapters and non-adapters was around 7,712 Nepalese Rupees.

Adapters also realized a significantly lower exposure to downside risk due to their decision. In our sample, households that adapted to climate change would have faced a downside risk of about 0.105 units higher (about 37 percent) had they not chosen to adapt to climate change. These estimates suggest that climate change adaptation decisions have an important role in hedging against losses due to unexpected climatic events.

5.7. Robustness check

In order to test the strength of our empirical results, several robustness checks for our main specification were conducted. First, we utilized the treatment effect model (Cong and Drukker, 2001; Cameron and Trivedi, 2005) to control the potential endogeneity of adaptation decisions. Results from the treatment model are consistent with the main results. In addition to using the treatment effect model, we report Propensity Score Matching (PSM) and Inverse Probability Weighted Regression Adjustment (IPRWA) estimates (presented in Appendix E) to check the robustness of the results. Results indicate that both crop revenue and downside revenue risk exposure are significantly higher for adapting households vis-à-vis the non-adapting households. The resulting estimates under the PSM and IPWRA models are consistent with those obtained using the ESR-CF approach. The results suggest an inability to control for unobservable effects in underestimating ATEs in the PSM. These findings are in line with earlier studies that validate the PSM's shortcomings in technology adoption literature (Andam et al., 2008; Shahzad and Abdulai, 2021). We also carried out a standard instrumental variable approach to estimate the impacts of adaptation decisions on crop revenue. The results are consistent with the findings under our main specification.

6. Conclusion

As global climate patterns change, farmers must make adaptation decisions to maintain the viability of their business operations while mitigating possible risk repercussions. Numerous potential adaptation measures are available at the farm level, depending upon the geographical regions, farming types, farm size, and household wealth. However, few studies explore the effectiveness of adaptation decisions in reducing the revenue risk.

[7] For brevity, we have not reported interaction between generalized residual and included exogenous variables.

Table 3
Estimation of downside revenue risk exposure.

Variable name	Skewness			
	Full sample OLS (1)	Full sample CF (2)	Adapters CF (3)	Non-adapters CF (4)
Male	−0.013	−0.014	−0.041	0.026
	(0.021)	(0.021)	(0.027)	(0.035)
Age (years)	0.003	0.003	0.008*	−0.001
	(0.003)	(0.003)	(0.004)	(0.004)
Household size (log)	0.002	0.002	−0.029	0.046
	(0.024)	(0.024)	(0.030)	(0.040)
Cultivated area (ha)	0.021***	0.022***	0.024***	0.015
	(0.008)	(0.008)	(0.009)	(0.013)
Educated	0.051**	0.050**	0.019	0.086**
	(0.023)	(0.023)	(0.028)	(0.037)
Access to credit	0.055***	0.052**	0.059**	0.043
	(0.021)	(0.021)	(0.026)	(0.033)
Irrigated land	0.069***	0.067***	0.038	0.108***
	(0.022)	(0.022)	(0.030)	(0.032)
Location-Terai[a]	−0.038	−0.043	−0.001	−0.084**
	(0.028)	(0.028)	(0.041)	(0.042)
Location-Mid-hill[a]	−0.003	−0.007	−0.007	−0.018
	(0.025)	(0.025)	(0.032)	(0.041)
Training/meeting attended	0.043**	0.041**	0.001	0.098***
	(0.021)	(0.021)	(0.030)	(0.031)
Annual temperature (°C)	0.014	0.013	−0.016	0.050
	(0.021)	(0.021)	(0.024)	(0.035)
Annual precipitation (mm)	−0.000	−0.000	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Total assets ('00,000 NPR)	0.001*	0.001**	0.001**	0.001
	(0.000)	(0.000)	(0.000)	(0.001)
Adaptation	0.017	0.064*		
	(0.022)	(0.036)		
Generalized residual		−0.043*	0.046	−0.105***
		(0.024)	(0.040)	(0.030)
Constant	−0.451***	−0.482***	−0.440***	−0.573***
	(0.091)	(0.094)	(0.117)	(0.140)
Observations	713	713	416	297
R-squared	0.072	0.075	0.056	0.170

Notes: CF represents the control function approach. Robust standard errors clustered at the village level are in parentheses. *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level. NPR represents Nepalese Rupee, Exchange rate: 1 US $ = Nepalese Rupees 106 at the time of survey (https://www.nrb.org.np/). The dependent variable "Skewness" refers to the third central moment of revenue function, which represents the downside revenue risk exposure.
[a]Of the three regions, Upper Hill is the excluded category in the geographical location dummy variable.

Table 4
Heterogeneity in crop revenue and downside exposure among adapters and non-adapters.

Sub-samples	Decision stage		Treatment effects (3)
	To adapt (1)	No to adapt (2)	
Crop revenue			
Adapting household	$\widehat{y_{11}} = 63009.434$	$\widehat{y_{10}} = 49976.675$	$\widehat{ATT} = 13032.759$***
Not adapting household	$\widehat{y_{01}} = 59963.010$	$\widehat{y_{00}} = 54642.625$	$\widehat{ATU} = 5320.385$***
Heterogeneous effects	$\widehat{y_{11}} - \widehat{y_{01}} = 3046.424$	$\widehat{y_{10}} - \widehat{y_{00}} = -4665.95$	$\widehat{ATT} - \widehat{ATU} = 7712.374$
Downside revenue risk exposure			
Adapting household	$\widehat{y_{11}} = -0.180$	$\widehat{y_{10}} = -0.285$	$\widehat{ATT} = 0.105$***
Not adapting household	$\widehat{y_{01}} = -0.215$	$\widehat{y_{00}} = -0.272$	$\widehat{ATU} = 0.057$***
Heterogeneous effects	$\widehat{y_{11}} - \widehat{y_{01}} = 0.035$	$\widehat{y_{10}} - \widehat{y_{00}} = -0.013$	$\widehat{ATT} - \widehat{ATU} = 0.048$

Note: ATT represents the effect of the adaptation on the households that adapted, while ATU represents the effect of the adaptation on the households that did not adapt *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level.

Using household survey data from Nepal and utilizing the control function approach in the endogenous switching framework, this study examines the economic gains realized from implementing climate change adaptation. In order to ensure the reliability of this study's empirical contributions, the analytical model was formulated with careful consideration provided to possible endogeneity issues arising from self-selection bias. Notably, our empirical framework distinguishes itself from similar earlier studies by adopting an estimation method that tackles previously unresolved challenges posed by endogeneity and self-selection issues in the sample data.

Our findings indicate that farmers' adaptation decisions are significantly influenced by structural, demographic, and social capital-related factors involving access to information, networks, and other useful community resources. Our analysis pursues adaptation decisions by

Table A.1
Climate change adaptation strategies used by the farmers.

Adaptation strategies	Frequency	Percentage
Adjusting planting and harvest date	105	25.24
Planting improved/ drought resistant/flood tolerant crop varieties	159	38.22
Mixed/intercropping cropping/crop diversification	173	41.59
Soil and water conservation techniques	108	25.96
Inorganic fertilizer/improved organic manure use	144	34.62
Application of herbicides/insecticides	94	22.6

Note: In our sample, out of adapting households, 279 households have practiced more than single adaptation strategies.

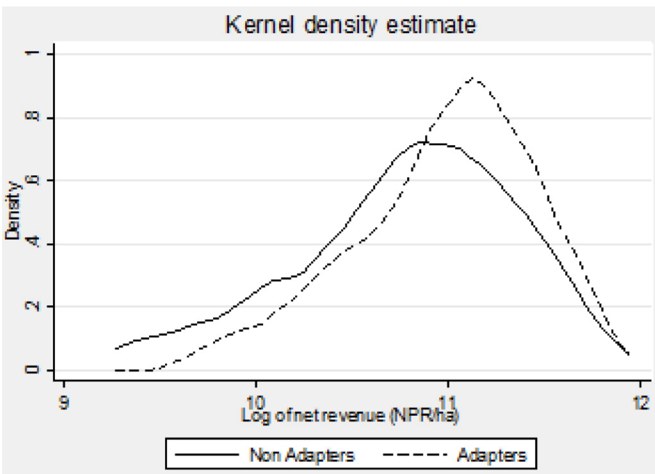

Fig. B.1. Distribution of crop revenue (log) between adapters and non-adapters.

establishing considerable benefits in the form of revenue enhancement and revenue risk reduction. Specifically, adapting farm households realize substantial and distinguishable gains in revenues and declines in risk levels relative to their non-adapting peer households.

As many farm economies start to acknowledge the reality of climate change and the urgency of risk-mitigating adaptation strategies that can be implemented at the farm level, this study's findings can serve as motivations for potential adaptation proponents. Our study clarifies and reminds us that efforts undertaken by microlevel units of societies, such as farms and households, are also crucial elements of the global crusade against worsening climate change repercussions. The 2020 United Nationals Environment Programme (UNEP) Adaptation Gap Report encourages more nature-based solutions aimed at restoring or maintaining the sustainability of ecosystems (United Nations Environment Programme (UNEP), 2021), a principle reflected in the climate change practices of this study's sample of farmers.

Moreover, our research can provide directional guidance for policy formulation by identifying important facets of social interactions and resource endowments that may elicit adaptation choices and enhance their potential return and risk benefits. Specifically, our study's results identify four potential drivers that can intensify farmers' climate change adaptation efforts. First, in this time of rapid progress in information technology, farmers' crucial access to crucial climate information can be expanded through, among others, deliberate institutional and industry efforts to extend broadband access to rural areas. Then, the government can prioritize rural development efforts that will minimize farmers' physical distance barriers to roads and markets. Finally, universities, non-government organizations (NGOs) and similar organizations can expand and implement more effective, efficient targeting schemes that will address the farmers' needs for greater access to extension and outreach.

These specific policy recommendations reinforce an argument highlighted in the 2021 Report of the United Nations Conference on Trade and Development (United Nations Conference on Trade and Development (UNCTAD), 2021). The contention posits that climate change adaptation is less of a risk management issue but more of a development planning stance. Indeed, the need for available and reliable infrastructures that link rural communities to important resources, markets, information, and services has been a perennial development issue that rested on the government's laps for ages. Such development thrust becomes even more pronounced and compelling as the climate

Table C.1
Validity of instruments.

Variable name	Crop revenue	Adaptation (1/0)	
	OLS (1)	Probit (2)	LPM (3)
Distance to the nearest market (minutes)	−0.001	−0.027***	−0.006***
	(0.002)	(0.005)	(0.001)
Distance to the nearest road (minutes)	0.030	−0.652***	−0.171***
	(0.090)	(0.129)	(0.034)
Climate information	0.019	0.599***	0.173***
	(0.073)	(0.113)	(0.031)
Distance to the nearest extension center (minutes)	0.001	−0.040***	−0.011***
	(0.002)	(0.005)	(0.001)
Constant	10.772***	1.288***	0.856***
	(0.081)	(0.147)	(0.037)
Observations	297	713	713
R-squared	0.002	0.309	0.347
LR chi2(4)		299.72	
F statistics			93.96

Robust standard errors clustered at the village level are in parentheses.OLS; Ordinary least square. LPM; Linear probability model. *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level.

Table D.1
Estimation of crop revenue using control function for adapters and non-adapters.

Variable name	Crop revenue (NPR)	
	Adopters (1)	Non Adapters (2)
Male	0.164***	0.297***
	(0.042)	(0.064)
Age (years)	0.006	0.021**
	(0.007)	(0.010)
Household size (log)	0.005	0.069
	(0.054)	(0.077)
Cultivated area (ha)	0.033**	0.040*
	(0.016)	(0.021)
Educated	0.076	0.210***
	(0.050)	(0.064)
Access to credit	0.171***	−0.005
	(0.043)	(0.063)
Irrigated land	0.098**	0.092
	(0.044)	(0.062)
Location-Terai	−0.050	0.120
	(0.054)	(0.078)
Location-Mid-hill	−0.158***	−0.012
	(0.052)	(0.079)
Training/meeting attended	0.116**	0.079
	(0.045)	(0.064)
Annual temperature (°C)	0.059	0.157**
	(0.048)	(0.063)
Annual precipitation (mm)	−0.000	−0.000**
	(0.000)	(0.000)
Total assets ('00,000 NPR)	0.002***	0.001
	(0.001)	(0.001)
Generalized residual	−0.259***	−0.014
	(0.069)	(0.065)
Constant	10.559***	9.620***
	(0.188)	(0.295)
Observations	416	297
R-squared	0.228	0.228

Note: Robust standard errors clustered at the village level are in parentheses. *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level. NPR represents the Nepali rupee; the exchange rate was USD 1 = 106 Nepali rupee at the time of the survey.

change agenda has become interspersed with economic development priorities.

Effective policies geared towards promoting optimized adaptation decisions will be instrumental in reverting the fallacy of the climate change reality while realizing longtime commitments to bring progress to rural communities. Our study is a reminder that while global leaders, industry bigwigs, and other institutional forces brainstorm, argue, and compromise to reach some consensus, smaller farm households in developing countries, like our Nepalese farming sample, consider microlevel solutions that hopefully will be worthwhile contributions to the containment of climate change – a serious global concern nowadays whose propagation they are actually the least responsible for.

This study's focus on the Nepalese farmers' climate change adaptation experiences should motivate further research efforts among similar smaller farm households in other developing countries. As this research clarifies through the Nepalese smaller households' example that climate change mitigation can reap both environmental and economic rewards, our hope is for many of their global peers to follow their lead.

CRediT authorship contribution statement

Chandra Dhakal: Conceptualization, Methodology, Formal analysis, Writing – original draft. **Savin Khadka:** Writing – original draft , Writing – review & editing. **Cheolwoo Park:** Writing – review & editing, Supervision. **Cesar L. Escalante:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

See Table A.1.

Appendix B

See Fig. B.1.

Appendix C

See Table C.1.

Appendix D

See Table D.1.

Appendix E

See Table E.1.

Table E.1
Estimation of farmers adaptation decision and its impact on crop revenue using treatment effect and matching methods.

Variable name	Adaptation(1/0) Probit (1)	Log(Crop revenue (NPR))[a] Treatment effect (2)	IV (3)
Male	−0.547***	0.243***	0.244***
	(0.131)	(0.040)	(0.037)
Age (years)	0.020	0.012*	0.012
	(0.018)	(0.007)	(0.008)
Household size (log)	0.023	0.025	0.025
	(0.157)	(0.044)	(0.034)
Cultivated area (ha)	0.292***	0.029**	0.028*
	(0.050)	(0.014)	(0.015)
Educated	0.444***	0.136***	0.134***
	(0.139)	(0.043)	(0.052)
Access to credit	0.213	0.097***	0.096**
	(0.131)	(0.037)	(0.039)
Irrigated land	0.229*	0.094**	0.094**
	(0.131)	(0.037)	(0.044)
Location-Terai	−0.935***	0.038	0.039
	(0.172)	(0.048)	(0.047)
Location-Mid-hill	−0.424***	−0.095**	−0.095*
	(0.164)	(0.044)	(0.050)
Training/meeting attended	0.290**	0.086**	0.086***
	(0.133)	(0.038)	(0.031)
Annual temperature (°C)	0.358***	0.093**	0.092**
	(0.135)	(0.041)	(0.046)
Annual precipitation (mm)	−0.000	−0.000*	−0.000*
	(0.000)	(0.000)	(0.000)
Total assets ('00,000 NPR)	0.014***	0.001**	0.001*
	(0.003)	(0.001)	(0.001)
Distance to the nearest market (minutes)	−0.027***		
	(0.006)		
Distance to the nearest road (minutes)	−0.365**		
	(0.152)		
Climate information	0.672***		
	(0.136)		
Distance to the nearest extension center (minutes)	−0.053***		
	(0.006)		
Adaptation		0.197**	0.203**
		(0.090)	(0.088)
Constant	0.307	10.021***	10.020***
	(0.543)	(0.176)	(0.224)
ATE^{PSM}	0.194		
	(0.038)		
ATE^{IPWRA}	0.137		
	(0.036)		
Observations	713	713	713
R-squared			0.205
Wald test of indep. eqns. (rho = 0): chi2(1) = 2.18 Prob > chi2 = 0.1397			

Note: IV represents the instrumental variable approach. Robust standard errors clustered at the village level are in parentheses. *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level.
NPR represents Nepalese Rupee, Exchange rate: 1 US $ = Nepalese Rupees 106 at the time of survey (https://www.nrb.org.np/).

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