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Adoption and Diffusion of Improved Technologies and Production Practices in Agriculture

Insights from a Donor-led Intervention in Nepal

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Abstract

Adoptions of improved technologies and production practices are important drivers of agricultural development in low-income countries like Nepal. There are still knowledge gaps concerning what determines the adoption of different types of technologies and practices, how information about them is diffused, and what general impacts the interventions promoting them are having. In this paper we partly close the gap, using data collected for evaluations of the Knowledge-Based Integrated Sustainable Agriculture in Nepal (KISAN) project led by USAID. We find that factors important to increasing the adoption of improved technologies and practices include improved access to markets, the role of the private sector in selling improved seeds and disseminating information, membership in progressive farmers' groups and cooperative societies, participation in agricultural training and farm visits, the provision of subsidies for seeds, and access to credit. Different factors are also found to affect the sources that farmers use for gathering information before adoption. The effects of KISAN projects vary significantly across the different crops grown, based on the evaluation models that address self-selection of both project participation and crop choices.

Keywords: Adoptions, Diffusions, Improved agricultural technologies and practices, Poisson regression, Bivariate probit inverse-probability-weighting, Nepal

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Acronyms

CBS	Central Bureau of Statistics
DAP	Diammonium phosphate
FTF	Feed the Future
IIDS	Institute for Integrated Development Studies
IPM	Integrated Pest Management
IPW	Inverse Probability Weighting
JICA	Japan International Cooperation Agency
KISAN	Knowledge-Based Integrated Sustainable Agriculture in Nepal
OLS	Ordinary Least Squares
RIDA	Research Inputs and Development Action
SUR	Seemingly Unrelated Regression
USAID	United States Agency for International Development
VDCs	Village Development Committees

1. Introduction

Increasing agricultural productivity through the adoption and diffusion of improved agricultural technologies and practices has been considered as one of the viable means for achieving economic growth and agricultural transformation (Evenson and Gollin, 2003; Gollin, 2010) in developing countries like Nepal. Nepalese agriculture is characterized by subsistence farming, the dominance of marginal and small farms, problematic access, low adoption of modern technologies, poor availability of inputs, lack of irrigation facilities, and limited investment in research and development (CBS, 2011). Due to the increasing outmigration of productive youths, there is also a shortage of labor in the agricultural sector. At the same time, farm mechanization rates remain low—less than 10 percent of agricultural households use modern machines for cultivation and post-harvest activities (CBS, 2011). All of this has resulted in low yields and low rates of agricultural commercialization. It is estimated that about 43 percent of agricultural entities are commercialized, leaving a majority of households (57 percent) still practicing subsistence farming (JICA, 2010).

The proportion of Nepali farm households using improved crop varieties is only about 33 percent (CBS, 2011). The annual application of DAP and urea, for instance, has been about 47 kilograms per hectare (kg/ha) and 63 kg/ha, respectively (Takeshima et al., 2016)—well below their average rates of application in the South Asia region. Consequently, promoting and facilitating the use of improved technologies and practices can be key strategies for increasing agricultural productivity and making agriculture a viable and sustainable source of livelihood in Nepal. Although studies have been conducted to assess the factors influencing the adoption in Nepal of improved varieties of rice (Ghimire et al., 2015) and maize (Ransom et al., 2003;

Paudel and Matsuoka, 2008; Ghimire et al., 2015), there are still knowledge gaps concerning what determines the adoption of different types of technologies and practices, how information about them is diffused, and what general impacts the interventions promoting them are having.

We partly close this gap by using data collected for the evaluation of the Knowledge-Based Integrated Sustainable Agriculture in Nepal (KISAN) project, which was led by USAID.[1] Specifically, we identify the factors influencing adoptions of improved technologies and production practices, factors affecting their diffusion, and the impacts of the KISAN project on farm productivity and the crops grown.

We have organized the remaining sections as follows. In the second section we discuss the data and methodology (e.g., survey procedure and sample size) as well as the descriptive statistics for the variables used in the analysis. In the third section we discuss the status, extent, and determinants of the adoption of agricultural technologies, as well as its intensity. We conclude in the last section with a discussion of policy implications.

[1] The KISAN project was implemented under the U.S. government's Feed the Future (FTF) Presidential Initiative, for which Nepal is a designated country. The overall goal of the FTF-Nepal strategy is to sustainably reduce poverty and hunger in the country. The FTF-Nepal iinitiative works in 20 lower hill and Terai districts in the Western, Mid-Western and Far-Western Development Regions of Nepal. It aims to increase agricultural productivity, reduce gap between potential and actual yields, facilitate farmers' access to markets, enhance income for the rural poor, and improve nutritional status in the country, especially of women and children. The FTF-Nepal initiative offers extension and advisory services for crops like paddy, lentils, maize, and high-value vegetables.

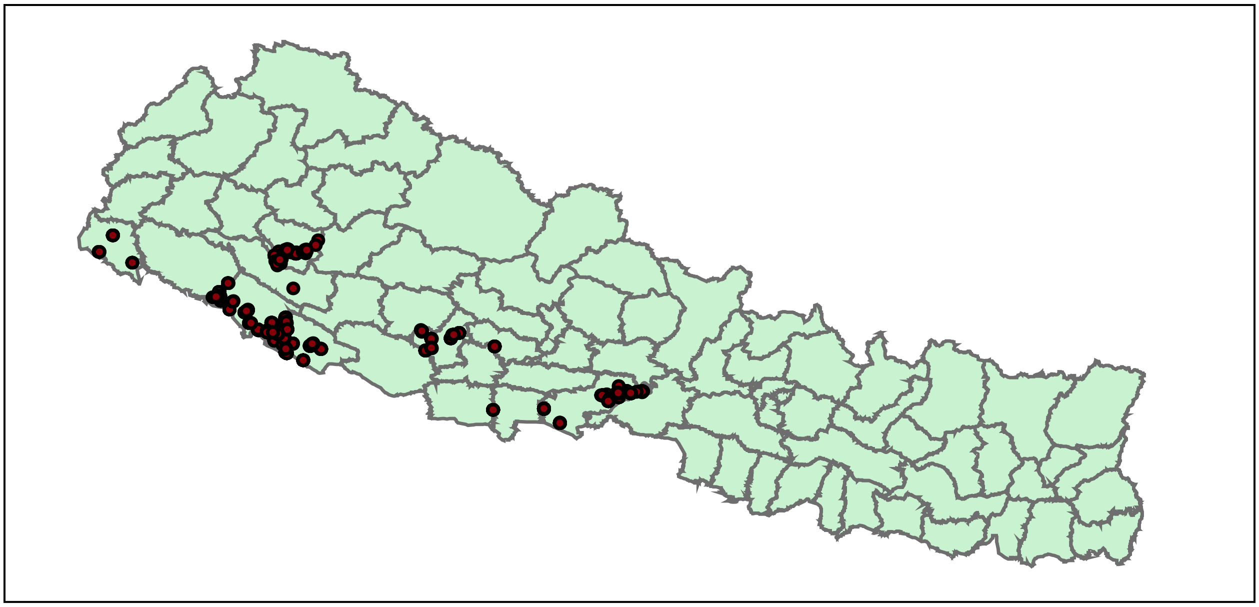
2. Data and Methodology

Our analyses are based on the primary survey data collected from the Hilly and Terai districts of western, mid-western, and far-western regions of Nepal. We selected six KISAN-intervention districts and one non-beneficiary district. The six intervention-districts were Gulmi from the western region, Banke, Bardiya, Dailekh, and Puythan from the midwestern region, and Kanchanpur from the far-western region. Since one of the study's four main objectives is to compare the outcomes between KISAN beneficiaries and nonbeneficiaries, we selected some of the Village Development Committees (VDCs) within the intervention districts as control VDCs along with Nawalparasi as a separate nonbeneficiary district. The districts were further divided into primary sampling units. The number of these sampling units across different districts was determined based on the proportion of FTF-beneficiary households.

We followed a multistage sampling technique. We surveyed 980 KISAN- beneficiary households from the KISAN-intervention districts and 980 households from the nonbeneficiary VDCs and the district Nawalparasi.

The data were collected from September to November of 2016. Figure 2.1 depicts the location of the interviewed households. Further, we also computed spatial data on the average monthly rainfall, ruggedness, and distance to rivers at the village level from various sources.

Figure 2.1: Locations of interviewed households in Nepal



Source: Compiled by the authors.

The variables selected include various agro-ecological and socioeconomic factors that have been found to be important drivers of improved production technologies and practices elsewhere. Several studies reveal a number of factors that influence adoption and diffusion, related to the characteristics of households, farms, institutions, and the environment. The earlier sets of policies were targeted to influence households through a series of intervening variables like agricultural trainings, field demonstrations, and delivery of agricultural extension services (Polson and Spencer, 1991; Ransom et al., 2003; Paudel and Matsuoka, 2008; Asfaw et al., 2012; Mariano et al., 2012; Ghimire et al., 2015). Since the household is the ultimate adaptor of a farm technology, household characteristics like experience in farming (Foster and Rosenzweig, 1995), household size (Marenya and Barrett, 2007; Noltze et al., 2012) and educational level of spouse (Teklewold et al., 2013) were found to be important determinants of technology adoption. Key farm characteristics include farm size (Ghimire and Huang, 2015), availability of inputs, and soil quality of the plot (Mason and Smale, 2013). Institutional factors, such as association with a farmers group (Ghimire and Huang, 2015), also help determine technology adoption, as do agro-ecological characteristics of farm location (Mason and Smale, 2013). Importantly, access to input and output markets (Ghimire and Huang, 2015; Langyintuo and Mungoma, 2008; Feleke and Zegeye, 2006), availability of resources and credits (Feder et al., 1985; Teklewold et al. 2012), and access to seed (Langyintuo and Mungoma, 2008; Ghimire et al., 2015) also influence technology adoption. Lastly, social networking has been found important in increasing adoption of improved technologies as well (Bandiera and Rasul, 2006; Conley and Udry, 2010; Foster and Rosenzweig, 1995; Krishnan and Patnam, 2014).

Table 2.1 presents the definitions and descriptive statistics of the variables used in the analysis. We have presented the mean value and standard deviation both for the full sample and for the beneficiary and nonbeneficiary households. We have also tested whether these characteristics significantly differ between the beneficiary and nonbeneficiary households. We find statistically significant differences for various variables. Later sections therefore address self-selection bias by employing suitable approaches.

Table 2.1: Definitions and sample averages of variables

Variables	Full sample (n = 1980)	KISAN-beneficiaries (n = 996)	Non-beneficiaries (n = 984)	
Uses cultural practices (1/0)	0.44	0.57	0.31	***
Uses pest management technologies, (1/0)	0.13	0.14	0.12	*
Uses disease management technologies (1/0)	0.06	0.06	0.05	
Uses irrigation management technologies (1/0)	0.24	0.24	0.23	
Uses climate-resilient technologies (1/0)	0.12	0.11	0.13	
Age of household head	47.83	45.93	49.71	***
Headed by male (1/0)	0.84	0.85	0.83	
Head has received formal schooling (1/0)	0.77	0.77	0.76	
Head has completed primary schooling (1/0)	0.19	0.19	0.19	
Head has completed intermediary degree or higher (1/0)	0.08	0.08	0.07	
Number of years involved in farming	21.42	19.17	23.64	***
Dependency ratio (#<15 and >65 years/household size)	0.33	0.33	0.33	
Household size	6.52	6.50	6.53	
Dalit ethnic group (1/0)	0.08	0.07	0.09	
Janajati ethnic group (1/0)	0.53	0.62	0.45	***
Upper castes (Brahmin, Chhetry) (1/0)	0.38	0.34	0.42	***
KISAN-beneficiary (1/0)	0.54			
Grows paddy (1/0)	0.80	0.84	0.76	***
Grows maize (1/0)	0.51	0.44	0.58	***
Grows lentil (1/0)	0.28	0.35	0.21	***
Grows cauliflower (1/0)	0.21	0.30	0.12	***
Grows tomato (1/0)	0.11	0.15	0.07	***
Marginal farmers (land size < 0.16 ha)	0.22	0.20	0.24	*
Small farmers (land size ≥ 0.16- < 0.33 ha)	0.25	0.27	0.23	**
Medium farmers (land size ≥ 0.33-1.0 ha)	0.39	0.38	0.39	
Large farmers (land size > 1 ha)	0.14	0.15	0.14	
log (value of livestock)	10.31	10.42	10.20	*
log (value of land)	-1.10	-1.09	-1.11	
Applies micro-nutrients (1/0)	0.13	0.11	0.15	***
Applies chemical fertilizers (1/0)	0.69	0.65	0.74	***
Has access to irrigation facility (1/0)	0.63	0.68	0.59	***
Receives subsidy (1/0)	0.08	0.11	0.06	
Takes loan (1/0)	0.47	0.46	0.49	
Receives seed information from farmers (1/0)	0.80	0.81	0.79	
Receives seed information from private sector (1/0)	0.19	0.19	0.20	
Receives seed information from cooperatives (1/0)	0.15	0.20	0.09	***
Member of a cooperative (1/0)	0.75	0.88	0.62	***
Member of a farmers group (1/0)	0.16	0.19	0.14	***
Member of a self-help group (1/0)	0.02	0.03	0.02	
Owns farm machinery (1/0)	0.10	0.10	0.09	
Receives agricultural advice (1/0)	0.55	0.79	0.31	***
Receives agricultural training (1/0)	0.42	0.64	0.19	***
Distance to nearest marketing center	2.88	3.26	2.51	***
Euclidean distance from the river	0.01	0.01	0.01	
Exposed to demonstration visit (1/0)	0.15	0.23	0.07	***
Terrain ruggedness index	174.37	167.44	181.21	
Standard deviation in annual rainfall	190.36	188.47	192.23	**
Average annual rainfall (mm)	123.25	115.67	130.73	***
Terai (1/0)	0.68	0.66	0.71	***
Hill (1/0)	0.32	0.34	0.29	***

Source: Authors.

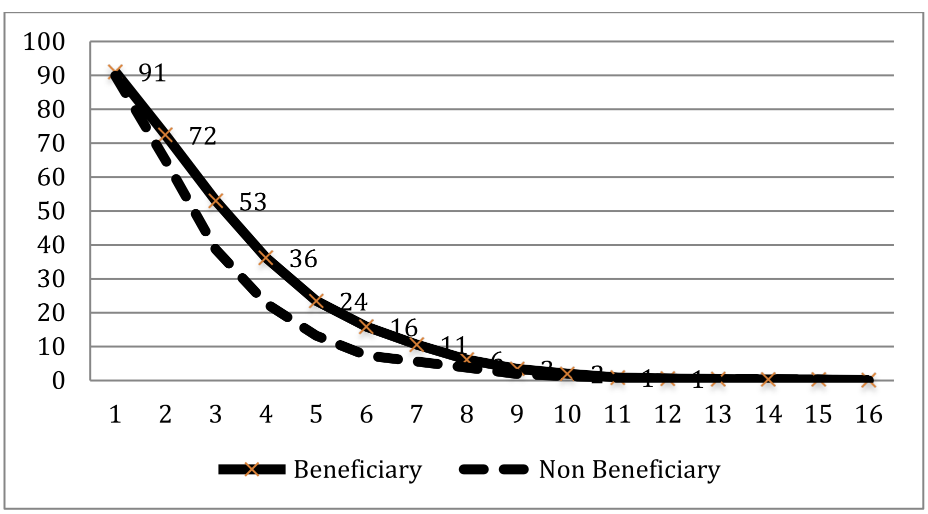
Note: Statistical significance at the *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$ levels.

3. Adoption of Improved Agricultural Farming Practices and Technologies in Nepal: Status, Extent and Determinants

3.1. Status and Extent

The KISAN project has promoted 31 improved farm technologies in Nepal. These farming practices are related to maximizing yields and minimizing post-harvest losses and risks, among other things, and have been broadly classified under these nine headings: (a) crop genetics; (b) cultural practices; (c) pest management; (d) disease management; (e) soil fertility management; (f) water management; (g) climatic effect mitigation; (h) agricultural marketing; and (i) post-harvest management. We inquired from the farmers about the extent of their adoption of these 31 different technologies. Figure 3.1 presents the number of technologies adopted by KISAN-beneficiary and nonbeneficiary households. On average, the farming households had adopted three technologies apiece. Only one-fourth of the households use at least five of these technologies. Generally, a higher proportion of beneficiary households use a greater number of technologies than non-beneficiary households.

Figure 3.1: Number of improved agricultural technologies used by KISAN-beneficiary and nonbeneficiary households *(percent)*

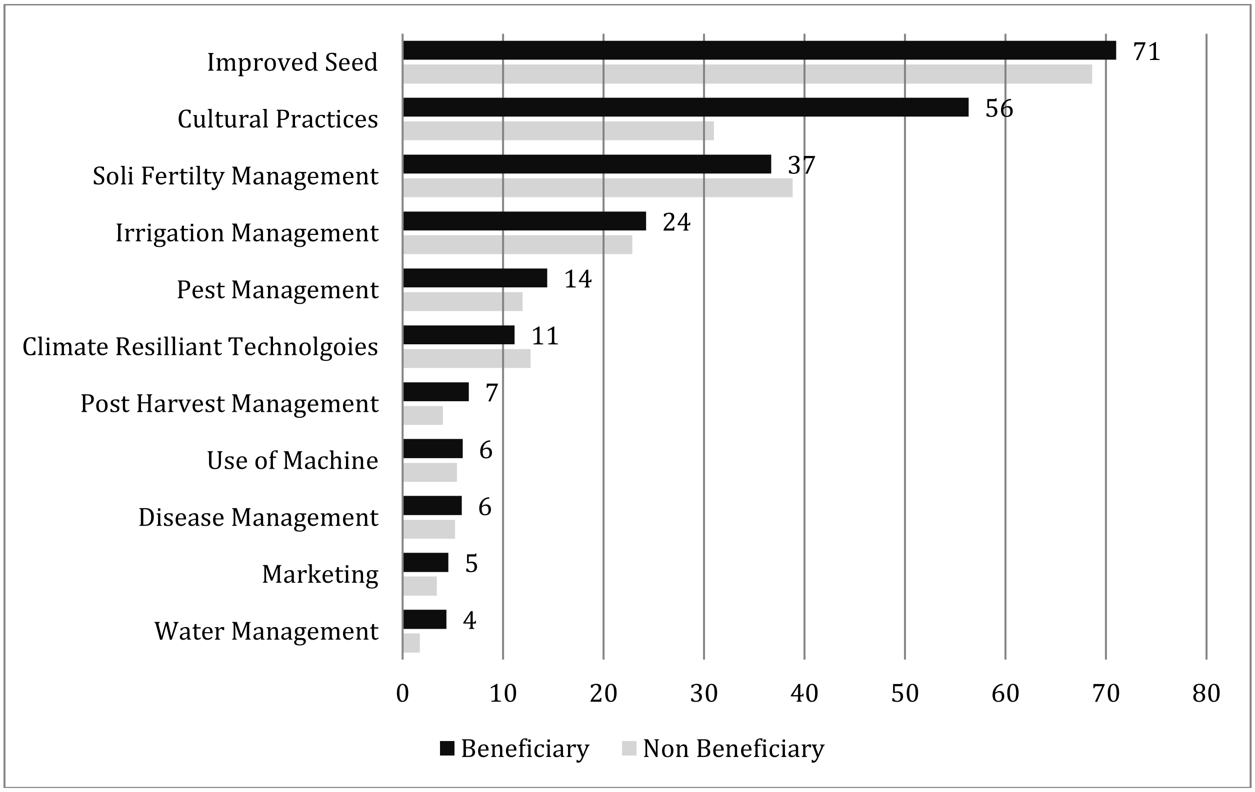


Source: Field survey, 2016.

Figure 3.2 presents the percentages of households that adopted each specific farm technology. The adoption of improved seeds was the most popular technology, practiced by about 70 percent of both KISAN-beneficiary and nonbeneficiary households. Other important farm technologies adopted by beneficiary households included cultural practices (adopted by 56 percent), soil fertility management (37 percent), and irrigation management (24 percent). The proportions of households adopting any of the remaining technologies were all less than 15 percent. Overall, the use of improved farm technologies was found to be higher among beneficiary than nonbeneficiary farmers.

Within each farm technology, there may be several improved farm practices. Therefore, the improved farm practices are considered as a subset of the improved farm technology. For example, the soil fertility management technology includes soil solarization, crop mulching etc.

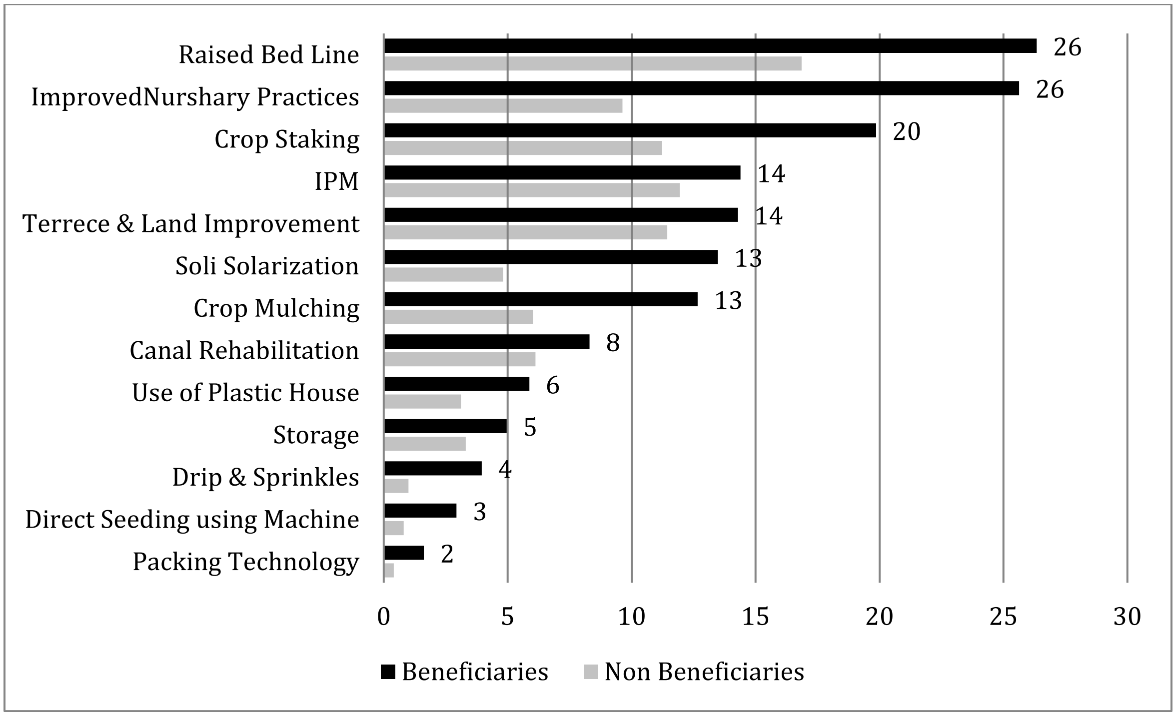
Figure 3.2: Percentage of KISAN-beneficiary and nonbeneficiary households adopting improved technologies



Source: Field Survey, 2016

Figure 3.3 summarizes the adoption status of improved farm practices. The farming practices adopted by more than 10 percent of the beneficiary households included raised bed lines (26 percent), improved nursery (26 percent), crop staking (20 percent), integrated pest management practices (IPM) (14 percent), terrace and land improvement (14 percent), soil solarization (13 percent), and crop mulching (13 percent). Generally, beneficiary households adopt more improved farm practices than nonbeneficiary households.

Figure 3.3: Percentage of KISAN-beneficiary and -nonbeneficiary households adopting improved practices



Source: Field Survey, 2016.

3.2. Determinants of the Intensity of Technology Adoption

3.2.1 Empirical framework

We first identify the drivers of improved technology adoption. We apply a Poisson regression model since the dependent variable is the number of technologies used by the farmers (count data). The earlier studies also used a Poisson regression model to study the factors influencing the adoption of the number of technologies (Ramirez and Shultz, 2000; Isgin et al., 2008; Pamuk et al., 2014). The Poisson distribution for the number of technologies adopted ($y = 1, 2, \dots, 31$) is given by the density equation,

$$\mathbf{Pr(Y = y) = \frac{e^{-\mu}\mu^{y}}{y!}}, \quad \mathbf{y = 0, 1, 2 \ldots, N} \tag{1}$$

where, μ is the average number of technologies adopted. The conditional mean function (μ) is

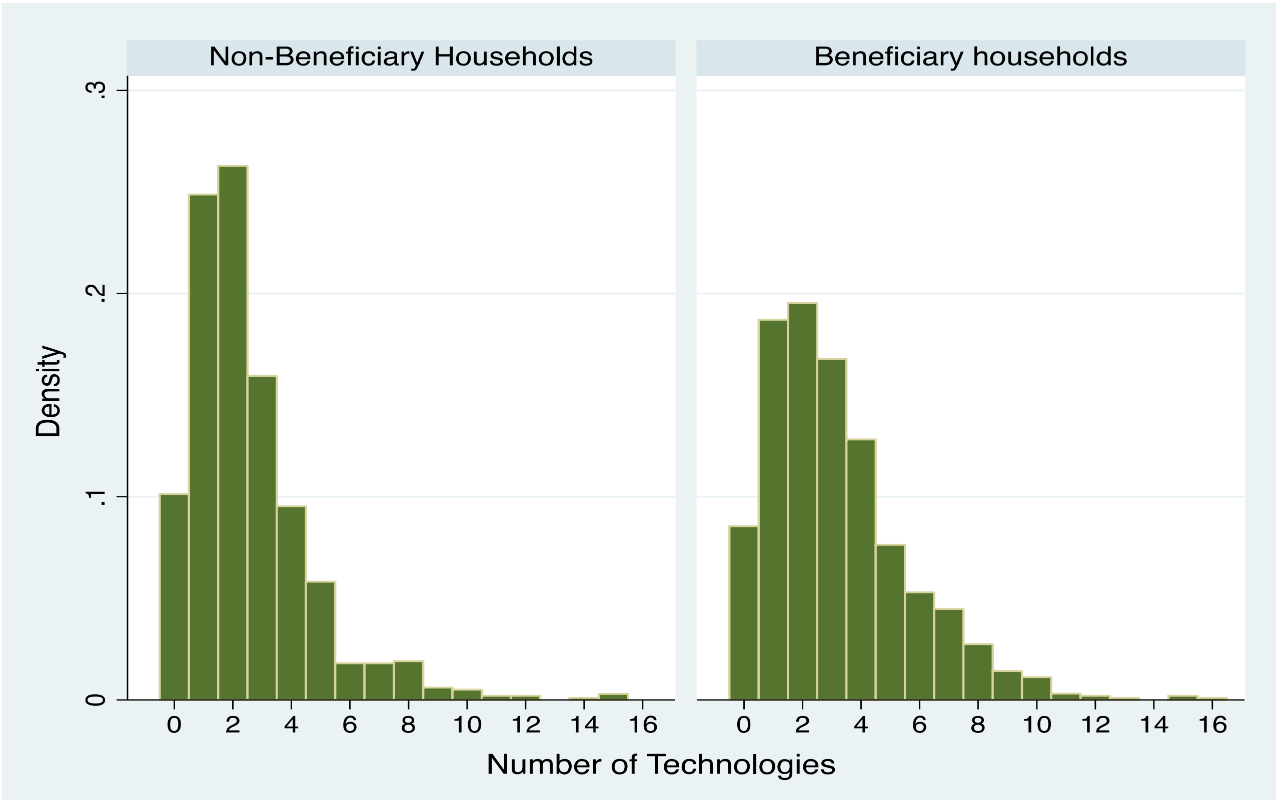
$$\mathbf{\mu_i = exp(x_i^{'}\beta)}, \quad \mathbf{i = 1, 2 \ldots, n} \tag{2}$$

in which *x* is an exogenous variable, including the constant.

3.2.2 Empirical results

We plotted the frequency of the number of technologies adopted by both KISAN-beneficiary and nonbeneficiary households. As illustrated in Figure 3.4, our response variable is not overdispersed. In our Poisson regression model, deviance goodness-of-fit test statistics and Pearson goodness-of-fit statistics are 2408.37 and 2305.63, respectively. We were not able to reject the null hypothesis at any level of statistical significance at which the data were Poisson-distributed.

Figure 3.4: Frequency of technology adoption by KISAN-beneficiary and -nonbeneficiary households, by number of technologies



Source: Authors.

Table 3.1 presents the estimated results of the Poisson model for both the full model and crop-specific models. All the coefficients may be interpreted as semi-elasticities since the equation (2) is in the form of log-linear model. The coefficient can be interpreted as the percentage change in the dependent variable given the unit change in the independent variable. We only interpreted coefficients that were statistically significant at least at the 10 percent level.

Table 3.1: Poisson regression estimates for the factors influencing technology adoption intensity

Variables	Full sample	Crop				
		Paddy	Maize	Lentil	Cauliflower	Tomatoes
Age of household-head	.0004	.0011	.0032	-.0007	.0017	.0018
Household is male-headed (1/0)	.0068	.1006*	-.0348	.1921**	.0827	.0586
Farming experience of head (years)	-.0016	-.0034*	-.0061***	-.0008	-.0037	-.0000
Head is illiterate (1/0)	-.0601	-.0723	-.1368**	.0405	-.1197	.0397
Head has completed intermediate / higher degree (1/0)	.0186	.0305	.0160	.0331	-.0351	.1499
Dependent ratio	-.1805**	-.2353***	-.1950*	-.2612*	-.3637**	-.3892**
Household size	.0060	.0104*	.0138*	.0033	.0134	.0012
Dalit caste (1/0)	-.0081	-.0950	-.1755**	.0249	-.1895	.1980
Janajati caste (1/0)	-.1350***	-.2410***	-.2568***	-.1768***	-.2797***	-.3811***
ln (Livestock asset)	.0114*	.0129*	.0056	.0110	.0002	-.0184
ln (Household landholding) (ha)	.0587**	.0591**	.0667*	.1059**	.1268**	.0851
Small farm (1/0)	.0963	.1202*	.1487*	.2234*	.1312	.2675
Medium farm (1/0)	.0180	.0285	.1216	-.0603	.0676	.1956
Proportion of land area with low quality of soil	.1289***	.0719*	.0110	.0776	.1203*	-.0536
Has access to irrigation facility (1/0)	.0223	.0135	-.0123	-.0656	-.0891	-.0713
Use chemical fertilizer (1/0)	.1404***	.0953*	.2372***	.0656	.1660**	.1772*
Use micronutrients (1/0)	.2771***	.2572***	.3021***	-.0008	.1937**	.0754
Distance to nearest market	-.0567***	-.0624***	-.1030***	-.0696***	-.0550**	-.0355
Cultivate maize (1/0)	-.0814*					
Cultivate lentil (1/0)	.0762**					
Cultivate cauliflower (1/0)	.1716***					
Cultivate tomato (1/0)	.1934***					
Seed subsidy (1/0)	-.0627	-.0325	-.0981	-.0456	-.0852	-.3133**
Received seed information from fellow farmer (1/0)	.0052	.1058**	.1273**	.0610	-.0122	.1381
Received seed information from the private sector (1/0)	.0742*	.1266***	.1102*	.0067	.2046***	.1300
Received seed information from the cooperative (1/0)	.1743***	.2247***	.1760***	.1553**	.1512**	.2010*
Took loan (1/0)	-.0352	-.0691**	-.0234	-.1293**	-.0629	-.0753
Cooperative member (1/0)	.0410	.0370	-.0694	.0683	.0023	.2178
Member of farmers organization (1/0)	.1101**	.1545***	.2881***	.1679**	.2716***	-.0149
Member of self-help group (1/0)	-.0196	.1416	-.1348	-.1206	-.2571	.2438
Owns farm machinery (1/0)	-.0187	.0704	.0430	.0267	.0822	-.0630
Seeks advice (1/0)	.2037***	.1280***	.2491***	.3619***	.1329	.2777**
Participates in agricultural training (1/0)	.3292***	.3064***	.3232***	.3604***	.2696***	.2913***
Participates in agricultural visit (1/0)	.1210***	.0784	.1154*	.0571	.1261*	.1511
Terrain ruggedness	.0001	-.0001	-.0002	.0000	-.0002	.0012***
Standard deviation in annual rainfall	-.0108**	-.0005	-.0045*	-.0055	-.0052	.0012
Average rainfall	.0048	.0043***	.0049***	.0038*	.0048*	-.0049
KISAN- beneficiary (1/0)	.0610	.1303***	.1402**	-.0217	.0197	-.2898**
Terai	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Regional fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations (No.)	1,980	1,589	1,011	549	411	217
Pseudo R^2	.13	.10	.14	.09	.11	.14
Wald chi^2	1254.1	653.84	617.18	198.14	206.90	134.42

Source: Authors.

Note: Statistical significance at the *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$ levels.

In the model, we included regional and district dummies to account for any regional and district fixed effects.

Concerning social caste[2] and wealth, we found the following. Janajati households adopt about 14 percent fewer technologies than do upper-caste households (Chhetry and Brahmin). Doubling the household's landholding (increasing the size by 100 percent) is correlated with a 5 percent increase in the number of technologies adopted.

Low soil quality is found to be positively correlated with the adoption of a higher number of technologies. This is because poor soils require more inputs, especially manures and fertilizers. Households already using chemical fertilizers and micronutrients adopt 14 percent and 27 percent more improved technologies, respectively.

An increase in the household's distance to market of one additional kilometer reduces the adoption of technologies by about 6 percent. When compared with paddy-growing households, maize-growing households adopt 8 percent fewer farm practices, whereas those cultivating lentil, cauliflower, or tomatoes adopt 8 percent, 17 percent, and 19 percent *more* improved farm practices, respectively.

Information and training clearly have an effect. Receiving seed information from fellow farmers, the private sector, or cooperatives helps to increase adoption of technologies or improved practices for most crops. Households belonging to farmers organizations also adopt more technologies for all crops, except tomatoes. Participation in agricultural training and field visits is associated with adoption of more improved farm practices for most crops.

Households receiving seed information from the private sector or from cooperatives adopt 7 percent and 17 percent more technologies, respectively. Those that belong to farmers'

[2] Broadly, the households can be categorised into three caste groups-Dalits, Janajati and Upper Castes.

organizations adopt 11 percent more improved farm practices. Households receiving agricultural training adopt 32 percent more technologies than nonrecipients, while those participating in agricultural visits adopt 12 percent more. In sum, agricultural trainings, demonstrations, and farm visits appear to be effective modes for promoting improved technologies among farmers.

We also estimated crop-specific models to find out whether the results from the full model vary across crops, and for all these models we accounted for the district, region, and agro-ecological fixed effects.

Some variables that are insignificant in the full model are found to be significant for certain crops. Among paddy and lentil growers, male-headed households tend to adopt more technologies. For paddy and maize crops, longer farming experience is actually associated with the adoption of fewer technologies. Among maize growers, those households with illiterate heads adopt 14 percent fewer technologies, and Dalit households adopt 18 percent fewer technologies than upper-caste households.

Larger family size is positively associated with adoption of more technologies across both paddy and maize growers. Compared to large farms, small farms adopt 12 percent, 15 percent, and 22 percent more technologies in the cultivation of paddy, maize, and lentil, respectively. The distance to market matters for all crops except tomatoes.

Greater rainfall is associated with adoption of more technologies, while households exposed to greater rainfall fluctuations adopt fewer technologies.

For paddy and maize, KISAN-beneficiary households were found to adopt more technologies. However, in the case of tomatoes, KISAN-beneficiary households were found to adopt *fewer* technologies.

3.3. Determinants of Specific Technologies Adoption in Nepal

3.3.1 Empirical framework

We now identify the determinants of the adoptions of specific technologies and practices from among the 31 technologies and practices promoted. Specifically, we focus on five promising technologies related to *cultural practices, pest management, disease management, irrigation management*, and *climate resilient* measures. We estimate these models using Ordinary Least Square (OLS) approach. Our models can be expressed as follows:

$$\mathrm{Cl} = \mathrm{a} + \beta \mathrm{Y} + \mu \quad (3)$$

$$\mathrm{P} = \mathrm{b} + \gamma \mathrm{Y} + \vartheta \quad (4)$$

$$\mathrm{D} = \mathrm{c} + \theta \mathrm{Y} + \varepsilon \quad (5)$$

$$\mathrm{I} = \mathrm{d} + \delta \mathrm{Y} + \epsilon \quad (6)$$

$$\mathrm{C} = \mathrm{e} + \alpha \mathrm{Y} + \varphi \quad (7)$$

where, $\boldsymbol{Cl}$, $\boldsymbol{P}$, $\boldsymbol{D}$, $\boldsymbol{I}$ and $\boldsymbol{C}$ are soil, pest management, disease management, irrigation management, and climate resilient technologies, respectively. Similarly, $\boldsymbol{a}, \boldsymbol{b}, \boldsymbol{c}, \boldsymbol{d}$, and $\boldsymbol{e}$ are the vectors of the constant, and $\boldsymbol{Y}$ is the vector of the farm/household, institutional and environmental characteristics expected to influence the choice of these technologies.

3.3.2. Empirical results

Table 3.2 presents the results. We interpret those coefficients that were statistically significant at the 10 percent level.

Table 3.2: Regression results from OLS models for factors influencing the adoption of specific technologies / practices

Variables	Cultural Practices	Pest management	Disease management	Irrigation management	Climate-resilient technologies
Age of household-head	.0048**	.0004	-.0007	.0011	.0002
Head is male (1/0)	.0817	-.0079	.0092	-.0340	-.0396*
Formal schooling of head (years)	.0960*	.0022	-.0466***	.0704**	.0218
Farming experience of household-head (years)	-.0085***	-.0007	-.0007	-.0032**	-.0002
Dependency ratio	-.1779*	.0346	-.0661***	-.0566	-.0145
Household size	.0050	.0013	.0029*	.0012	.0029
Marginal farm households (1/0)	.0071	.0159	.6003***	-.0334	.0717
Small farm households (1/0)	-.0220	.0023	.6156***	-.0857	.0284
Medium farm households (1/0)	-.1283	-.0002	.5983***	-.0190	.0226
Dalit caste (1/0)	-.0018	-.0670**	-.0338*	-.0971**	-.0405
Janajati caste (1/0)	-.2400***	-.0653***	-.0141	.0132	-.0658***
ln (Livestock assets)	-.0008	.0016	.0018	.0062	.0032
ln (Land value)	.0324	.0184	.0007	.0256	.0098
Proportion of area with low quality soil	.0214	.0691***	-.0061	.0750***	.0215
Has access to irrigation facility (1/0)	-.0481	-.0529***	-.0028	.0680**	.0085
Distance to nearest market	-.0581***	-.0123***	-.0095***	.0064	-.0067
Seed subsidy (1/0)	-.0941	-.0503*	-.0026	-.0148	.0346
Took loan (1/0)	-.0267	-.0257*	-.0062	.0383	-.0413***
Cooperative member (1/0)	.0255	-.0204	-.0098	.0085	.0254
Member of farmers organization (1/0)	.3830***	.0212	.0096	.1879***	.0223
Member of self-help group (1/0)	.1232	.0127	.0455	-.0679	-.0641
Owns farm machinery (1/0)	-.0291	-.0296	-.0212	-.0551	-.0219
Seeks advice (1/0)	.1718***	.0171	.0398***	.0377	.0034
Participates in agricultural training (1/0)	.3169***	.0911***	-.0078	.0682**	.0506***
Participates in agricultural visit (1/0)	.0377	-.0155	.0605***	.0815**	.0509**
Terrain ruggedness	.0002*	.0001***	-.0001***	.0000	-.0001*
Standard deviation in annual rainfall	-.0064***	.0012	-.0044***	-.0057***	-.0004
Average rainfall	.0034**	-.0010*	.0031***	.0055***	.0018***
Cultivate paddy (1/0)	.1888***	-.0023	-.0006	.1151***	.0352
Cultivate maize (1/0)	-.0598	.0116	-.0098	-.0037	-.0306
Cultivate lentil (1/0)	.0241	.0534***	.0052	.0090	.0006
Cultivate cauliflower (1/0)	.3356***	.0401**	.0357***	.0169	.0394**
Cultivate tomato (1/0)	.4921***	.1632***	-.0032	-.0232	.0768***
KISAN- beneficiary (1/0)	.2359***	-.0241	.0069	-.0189	-.0367*
Constant	Yes	Yes	Yes	Yes	Yes
Observations (No.)	1,979	1,979	1,979	1,979	1,979
R-squared	.2343	.1055	.0865	.0936	.0576

Source: Authors.

Note: The figures in parentheses are standard errors. Statistical significance at the *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$ levels.

Concerning the characteristics of households, we find the following. Households headed by older adults are more likely to adopt soil-related technologies than households with younger heads, although this effect is insignificant for the other technologies. Female-headed households are 4 percent more likely to adopt climate-resilience technologies than male-headed households. Households headed by adults with formal schooling, as compared with households headed by adults without it, are 10 percent more likely to adopt cultural practices, 7 percent more likely to adopt irrigation management technologies, and 5 percent more likely to adopt disease management technologies. The greater adoption of disease management technologies may be due to the fact that educated households might be trying to avoid the use of chemicals and sprayers due to their awareness of the potential adverse effects on human health as well as the environment.

Concerning castes, Dalit and Janajati families are less likely to adopt the majority of these technologies than households in the Brahmin, Cheetry, and other caste groups. Dependency ratios are negatively associated with the adoption of cultural practices and disease management technologies. Households with larger family sizes are more likely to adopt disease management technologies.

Surprisingly, longer experience farming is correlated with lower rates of adoption of some technologies, including cultural practices and irrigation management technologies. This may be because these technologies have been introduced recently and older farmers are less likely than younger ones to quickly adjust to or switch to using them.

Additional findings concerning farm size, location, and experience are as follows. Marginal, small, and medium-size farms are more likely to adopt disease management technologies than larger farms. Better proximity to the nearest market leads to greater adoption of cultural practices, pest, and disease management technologies, underscoring the importance of market access. Unsurprisingly, households with access to irrigation facility are more likely to adopt irrigation management practices.

Households receiving seed subsidies are less likely to adopt pest management technologies; this may be because these households purchase pest-resistant crop. Similarly, households receiving loans are less likely to adopt pest management and climate resilient technologies. The last finding may be explained by the fact that only a small number of farmers took loans for agriculture-related purposes, but a larger number took loans to smooth out their household consumption during food-deficit seasons.

Findings concerning training and information sharing are as follows. Households belonging to farmers groups are more likely than other households to adopt cultural practices and irrigation technologies. Those seeking agricultural advice are 17 percent more likely to adopt cultural practices and 4 percent more likely to adopt disease management technologies than those not seeking advice. Households receiving agricultural training are 32 percent, 9 percent, 7 percent, and 5 percent more likely to adopt cultural practices, pest management, irrigation management, and climate resilient technologies, respectively, than households receiving no such training. Similarly, households participating in farm visits are 6 percent, 8 percent, and 5 percent more likely than nonparticipating households to adopt disease management, irrigation management, and climate resilient technologies, respectively.

Concerning terrain and weather, we find the following. Greater terrain ruggedness is positively associated with the adoption of cultural practices and pest management technologies, but is negatively associated with the adoption of disease management and climate resilient technologies. Households with a higher proportion of land with poor cultural practices are more likely to adopt pest and irrigation management technologies than households with lesser amounts of poor cultural practices. Greater *rainfall uncertainty* is negatively associated with the adoption of cultural practices, disease, and irrigation management technologies, whereas *greater rainfall* is positively associated with the adoption of the same (but not with pest management) technologies.

Results also vary across crops. For paddy growers, we find 19 percent and 12 percent higher probability of adopting cultural practices and climate resilient technologies, respectively. However, for maize growers, none of the improved farm practices was found significant. Lentil growers are about 5 percent more likely to adopt pest management technologies. Cauliflower-growers are 34 percent, 4 percent, 4 percent, and 4 percent more likely to adopt cultural practices, pest management, disease management and climate resilient technologies, respectively. Similarly, tomato growers are 49 percent, 16 percent, and 8 percent more likely to adopt cultural practices, pest management and climate resilient technologies, respectively. The KISAN-beneficiary households are 24 percent more likely to adopt cultural practices, but 4 percent less likely to adopt climate resilient technologies.

3.4.Factors associated with the diffusion of improved varieties and production practices

Farmers adopting improved technologies and practices typically rely on certain information sources before their adoption, either because they prefer one source over another or simply because they lack access to other types of information. It is therefore quite important to identify those information sources that might be more effective in inducing adoptions.

Because knowledge of improved varieties or practices is revealed most vividly when they are adopted in practice, the diffusion processes can typically be assessed only by observing farmers who have adopted them. In the following analysis, determinants of the key information sources for each improved technology and improved production practice are estimated considering all these aspects.

3.4.1 Estimation method

Our data include no variables on households' awareness of each type of technology or practice. Instead, the data report the primary sources of information from those who had actually adopted the technologies or practices. The data also capture whether a household has sought agricultural information in general from a formal source. We utilize these sets of variables for the analysis.

To assess the relationship between important sources of information for specific technologies / improved practices and the characteristics of the farmers, we applied the following empirical model:

$$\boldsymbol{s_{ij}} = \boldsymbol{f}(\boldsymbol{X}), \tag{8}$$

where $\boldsymbol{s_{ij}}$ is the indicator of whether the household learned about technology or practice $\boldsymbol{i}$ from source $\boldsymbol{j}$, and $\boldsymbol{X}$ denotes the household's characteristics. A multinomial logit method was used to estimate equation (8).

An empirical challenge in estimating equation (8) is that the information source $\boldsymbol{j}$ that farmers rely on is only observed if the farmer adopts the relevant technology or practice $\boldsymbol{i}$. Estimating without taking into account such mechanisms would lead to biased estimates. One way bias can be addressed is by applying sample selection models, in which we estimate how $\boldsymbol{X}$ affects the probability of adoption of technology / improved practice $\boldsymbol{i}$ by the household through standard methods like Probit. We then incorporate the estimated probability into the estimation of equation (8). In particular, we apply the inverse probability weighting (IPW) method (Wooldridge 2007).

We focus on the technologies and practices that have been relatively widely adopted in the study area; namely, *improved seeds, cultural practices, soil fertility management, irrigation management, pest management,* and *climate resilient practices*[3]

3.4.2 Results

Tables 3.3 and 3.4 summarize the estimation results as to which household characteristics affect the probability of relying on information from (i) informal sources (neighboring farmers, family, friends); (ii) cooperatives / farmers' organizations; (iii) public extension services; and (iv) private extension services. By the design of the estimation methods, these results show how each factor affects the probability of receiving information from the households (given their characteristics) about improved technologies from each source, *regardless of whether they actually adopt such improved technologies or not.* The figures have been shown as marginal effects on the probability (with 1 = 100 percent) that a household relies on each source of information.

The key patterns of diffusion we find are as follows.

With greater experience in farming, farmers tend to obtain information from informal sources instead of through group members in farmers' organizations.

Membership in a farmers' organization generally raises the likelihood of receiving information from a household belonging to that group, or from the public sector, concerning information on various technologies including improved seeds and soil fertility improvement practices. Meanwhile, membership in a farmers' organization reduces the likelihood that such information is obtained from informal sources. Additionally, receipt of formal credit is

[3]Here, we exclude "disease management" whose adoption relatively less common, and exhibited insufficient variations in diffusion patterns required for the analyses. We, however, add "cultural practices" for the analyses here, to gain richer insights into the difference in diffusion patterns across different technologies and production practices.

associated with a greater likelihood of receiving information through a farmers' organization rather than from informal sources.

The experience of being exposed to demonstrations or training in the past leads to a greater likelihood of receiving information from the public sector.

Farmers living closer to a market tend to rely more on informal sources, while those living farther away from a market tend to rely more on the members of farmers groups they are associated with.

Information sources are sometimes associated with specific agro-ecological conditions, and this may very across the types of improved technologies. For example, the public sector is a significant source of information for improved soil fertility management practices in the areas covered with Cambisols, Fluvisols / Greysols, or Phaeozems soils. However, in those areas the public sector is not a particularly significant source of information for the improved seeds or other cultural practices.

Ownership of telephones, which also indicates access to internet communications and technology, significantly induces farmers to obtain information from formal sources, including other members within farmers' groups. In some cases it induces farmers to obtain information from public sector sources, including extension service agents, as well as from private-sector extension officers.

Table 3.3: Factors affecting the probability of receiving information about improved technologies from each source (only showing statistically significant coefficients)

Improved technologies / improved practices [a]	Sources of information on *improved seeds*				Sources of information on *cultural practices*				Sources of information on *soil fertility management*			
Factors	Informal	Group	Public sector	Private sector	Informal	Group	Public sector	Private sector	Informal	Group	Public sector	Private sector
Share of adopters within the area						.017*	.008*					
Shares using cooperative / farmer organizations	-.006***	.004***			-.038***	.013***						-.020***
Shares using public extension services		-.003**							-.038**			.019***
Shares using private extension services	-.004*			.001*								
ln (total area owned)						-.105***	-.031†					
Average distance to the plot					-.058*							
ln (number of plots)		.054*				.055*	.029*			-.054**		.028†
Age of household-head		.003***		-.001*						.001*		
Gender of household-head					-.120*		-.052**			.062**		
Education level of household-head	.015†			.005†				.003**				
Farm experiences of household-head	.003*	-.005***		.001**	.006**	-.003**				-.003***		
Adult male members in household	.028**	-.019**				.014†						-.013**
Adult female members in household							.013***		.047***	-.016**		-.012**
ln (amount of remittances received)	-.005†	.004*					.002*	.001*	.007**	-.005**		
ln (total household assets)	.018†							-.008***				
ln (total livestock assets)								.003†			.011**	.007***
Whether receiving credit (1 = yes)	-.051†	.053**				.045*		013***				
ln (market distance)						.074***			-.059**	.040***		
Received information from public sector	.087**						-.031†					
Whether exposed to demonstrations in the past	-.100**	.061*	.070**	.025*				.018***				
Whether exposed to trainings in the past	-.192***	.143***			-.245*	.198***	.111***	-.211***		.123**	.098***	-.308***
ln (rainfall)												
Distance to the nearest river												
ln (terrain ruggedness)												
ln (distance to India)												
Owns a telephone	-.250***	.161***	.065***	.057***	-.242***	.127***	.041*		-.160***	.051*		
Soil is Cambisols								.025*				
Soil is Fluvisols / Greysols					.236**			-.017*				
Soil is Phaeozems							.079**					.032*
Membership in a farmers' organization	-.182***	.087***	.038**	.030**		.057**		.017***		.047*	.029†	
District dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Caste dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size (No.)	1340				806				732			

Source: Authors.

Note: Information sources defined as follows: *Informal* = friend, farmer who is a neighbor, relative/ family outside the household; *Group* = cooperatives / farmers' organizations; *Public sector* = public sector extension officer, agri-exhibitions, agri information center; *Private sector* = private sector extension officer. Statistical significance indicated as follows: *** = 1%; ** = 5%; * = 10%; † = 15%.

Table 3.4: Factors affecting the probability of receiving information about improved technologies from each source (only showing statistically significant coefficients)

Improved technologies / improved practices	Sources of information on *irrigation management*				Sources of information on *pest management*				Sources of information on *climate resilient practice*			
Factors	Informal	Group	Public sector	Private sector	Informal	Group	Public sector	Private sector	Informal	Group	Public sector	Private sector
Share of adopters within the area	.093***	-.144***	.003*				.341**	.000		.069***		
Shares using cooperative / farmer organizations			.014†			.014***	-.029*	.000		-.048***		
Shares using public extension services	-.168***	.031†			.027***	-.027***	-.008*				-.031**	
Shares using private extension services	-.073*	.061***		.014†	.016†							
ln (total area owned)			-.035*			-.118*	-.063†				-.103**	
Average distance to the plot					-.062*					-.052**	.039***	
ln (number of plots)	.146**	-.063*	.047**			.087*				.069†	.044*	
Age of household-head		.003***		-.002*							.003*	
Gender of household-head			-.219***	.046†								
Education level of household-head				.009***							-.009*	
Farm experiences of household-head		-.003***		.003***					.006**	-.004**		
Adult male members in household		-.017*					.020***					
Adult female members in household	.044**	.010*										
ln (amount of remittances received)	.012**	.004*		-.005†								
ln (total household assets)	-.053***						.019†			.034**		
ln (total livestock assets)	-.043***	.063***	.019*	-.007**							.030**	
Whether receiving credit (1 = yes)												
ln (market distance)					-.091***	.083***	-.048*					
Received information from public sector					-.112†				.132*		-.084**	
Whether exposed to demonstrations in the past		.125***				.078**	.045†			-.055†		
Whether exposed to trainings in the past			.086**	-.452***	-.236**					.122*	.075†	
ln (rainfall)												
Distance to the nearest river												
ln (terrain ruggedness)												
ln (distance to India)												
Owns a telephone									-.319***		.134***	
soil is Cambisols					-.139*	.111†	.174***		-.163**			
Soil is Fluvisols / Greysols					-.318***						-.770***	
Soil is Phaeozems					-.301***		-.137**					
Membership in a farmers' organization	-.108*				-.123***				-.175***	.155***		
District dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Caste dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample (No.)	464				265				239			

Source: Authors.
Note: Information sources defined as follows: *Informal* = friend, farmer who is a neighbor, relative/ family outside the household; *Group* = cooperatives / farmers' organizations; *Public sector* = public sector extension officer, agri-exhibitions, agri information center; *Private sector* = private sector extension officer. Statistical significance indicated as follows: *** = 1%; ** = 5%; * = 10%; † = 15%.

3.5. Impact Assessment of KISAN Project Participation

We now estimate the impacts of KISAN projects on various outcome indicators, using the standard impact evaluation methods.

The farm-level economic impact assessment uses the following parameters. Crop revenues are the aggregate revenues from the production of rice, maize, lentils, cauliflower, and tomatoes. The crop production cost is the sum of the following five costs:

1. Materials costs, including costs of seeds, seedlings, chemical fertilizer (urea, DAP, potash, other chemical fertilizer), micro-nutrients, manure, pesticides, and other miscellaneous materials;
2. Labor costs, including the opportunity costs of family labor evaluated at the wage rate, and the costs of labor used for plowing, other land preparation, sowing, transplanting, irrigation, weeding, spraying, manure-spreading, harvesting, threshing, and other operations;
3. Animal costs, including costs of animals used for plowing, threshing, and other uses, evaluated at reported rental costs;
4. Costs of services done by machineries, that include the costs of machine-based services for plowing, harvesting, threshing, pumping by diesel pumps and electric pumps, and other machine-based service costs; and
5. Other costs, including expenditures on the collection, packaging, and transportation of produce, costs paid for leased-in land, land revenue taxes, and any other costs.

The impacts are estimated through treatment models similar to those used in the previous sections but with some extensions to incorporate the complexities associated with various economic indicators, such as incomes and their relations with cropping choices. In particular, we use IPW methods and their extensions, which have been increasingly used in the literature for estimating the treatment effects under a variety of conditions, including for the agricultural sector in Nepal (Wooldridge 2007; Imbens and Wooldridge, 2009; Takeshima, 2017; Takeshima et al., 2017).

First, we identify the factors $\mathbf{z}$ associated with the binary indicator $\mathbf{I}$ of whether a household participates in the KISAN project (or a certain component of the project), that is,

$$\boldsymbol{I} = \boldsymbol{f}(\boldsymbol{z}), \tag{9}$$

which is estimated by standard discrete dependent-variable models, like probit or multinomial logit (if there are more than one type of project that the household can participate in). From this, the probability that a household would participate in the particular project $\boldsymbol{p}$ is estimated. We calculate $w = 1/p$.

Then, for samples in each treatment status, we estimate the determinants of key outcome indicators $\boldsymbol{y}$,

$$y = g(x) \text{ with weights } w, \tag{10}$$

in which $\boldsymbol{x}$'s are the possible factors likely to affect the variations in $\boldsymbol{y}$.

Then, the intercepts estimated in equation (10) are compared across different treatment statuses. If $\boldsymbol{x}$ contains only a constant, the estimator leads to the standard average treatment effects. Otherwise, equation (10) is an IPW regression adjustment model, which further improves the balancing properties of samples across treatment statuses (Imbens and Woolridge, 2009; Austin, 2011).

3.5.1 Inverse Probability Weighted Model with Bivariate Probit

Evaluations of project impacts on economic outcomes such as revenues and costs by crops must account for the potential endogeneity of crop choices. This is addressed by combining a bivariate probit model with the IPW model. In bivariate probit models, we first estimate the probability that the household grows rice, for example, in addition to whether the household participates in the project or not. We then estimate $\boldsymbol{p}$ for two cases: (i) the probability that a household grows rice and participates in the project; and (ii) the probability that a household grows rice but does not participate in the project. Using these modified probability parameters, we may proceed with the IPW methods, as described above.

3.5.2 Results

Table 3.5 summarizes the average impact of participating in the KISAN project. The figures shown are rates of increase in the key indicators due to participation in the project (a growth rate of 1 indicates a 100 percent increase in, or doubling of, the indicators).

We find the following. Participation in the KISAN project generally has had a significantly positive impact on crop revenues (in both aggregate and per- hectare terms), on the order of about 20 percent. At the same time, participation in KISAN did not significantly increase production costs. The project therefore is likely to have increased farmers' net profit from crop production. The effects are also observed consistently across both male-headed and female-headed households.

Table 3.5: Average impact of KISAN project participation on crop production costs and farm revenue (1 = 100% increase)

Indicator	All households	Male-headed households	Female-headed households
Crop revenues	.170***	.113***	.216†
Crop production costs	-.050	-.051	-.006
Crop revenues per hectare	.236***	.181***	.317**
Crop production costs per hectare	.024	.019	.075

Source: Authors.
Note: Statistical significance indicated as follows: *** = 1%; ** = 5%; * = 10%; † = 15%.

Impacts of KISAN Project on Crop-specific Productivity

Table 3.6 summarizes the average impact of the KISAN project on various productivity indicators for rice, maize, and lentils. These estimates control for the farmers' endogenous decisions on participating in KISAN project and their endogenous decisions on whether to grow a certain crop or not.

The impacts on productivity differ across crops. While the KISAN project has significantly influenced various productivity indicators for rice and maize crops, its effects on lentils are generally ambiguous. The crop-specific interventions are therefore important in achieving impacts on the productivity of a particular crop.

In addition, while the effects on rice and maize crops are generally positive, they occur through potentially different mechanisms. For rice, the project raised the production value per hectare, but this was largely enabled by the increase in the prices farmers received rather than from yield increases. The increase in rice price might be due to the shift from low-value varieties to the high-value varieties in greater demand by consumers. There has also been an efficiency benefit, as is indicated by the reduced cost of rice production per hectare, suggesting that the new rice varieties have enabled these farmers to achieve similar yields with significantly lower use of inputs.

The effects on maize crops are primarily achieved through increased revenues per hectare through combination of positive (although statistically insignificant) effects on both yield and prices. Although reductions in production costs per hectare are also observed, this has been estimated less precisely due to relatively larger variations in cost figures observed across maize producers as compared with rice producers.

Table 3.6: Impact of KISAN Project on crop productivity and production costs of major crops (1 = 100% increase)

Outcome indicator	Sample	Crop			
		Rice	Maize	Lentil	Cauliflower
Crop revenue per hectare		.120*	.337**	.198	-.017
	Male-headed households	.142*			
Production cost per hectare		-.228***	-.255*	.034	.624
	Male-headed households	-.238***			
Price relative to other crops		.062**	.076	-.183	.205***
	Male-headed households	.075*			

Source: Authors.
Note: The estimates were obtained through the Inverse Probability Weighting methods, combined with bivariate probit model.
The statistical significance may be lower depending on the actual standard errors, whose calculations are complicated. Statistical significance indicated as follows:
*** 1%,** 5%, *10%, and †15%.

4. Conclusions and Policy Implications

Nepal has been designated as a participant in the U.S. government's FTF Presidential Initiative due to the country's prevailing high poverty rate and chronic food insecurity. The FTF initiative intervened in 20 lower Hill and Terai districts in the Western, Mid-Western and Far-Western Development Regions of Nepal. The FTF initiative aims to increase agricultural productivity, reduce the gap between potential and actual yields, facilitate farmers' access to markets, enhance income for the rural poor, and improve nutritional status in Nepal, especially among women and children. To meet these goals, the KISAN project has been actively implementing various programs in the FTF-beneficiary districts to promote improved and modern technologies. In this paper we have empirically analyzed the adoption and diffusion of agricultural technologies (improved varieties and farm practices) promoted under the project.

Using a Poisson model, we find that the intensity of technology adoption is *positively* associated with land size, soil quality, use of chemical fertilizers, use of micro-nutrients, livestock assets, sources of seed information (from private sector and cooperatives), membership in farmers' organizations, and participation in agricultural training and farm visits. Adoption of improved technologies is *negatively* associated with greater dependency ratios in households, longer distances from households to the nearest market, and increases in the standard deviation of annual rainfall (weather risk).

Among five important technologies (cultural practices, pest management, disease management, irrigation management, and climate-resilient technologies), the KISAN-beneficiary households displayed an approximately 24 percent higher probability of adopting cultural practices. We further find that different characteristics are significantly associated with the adoption of different types of technologies.

Regarding cultural practices, higher probabilities of adoption are associated with increases in the age and educational level of the household head, affiliation with farmers' organization, participation in agricultural training, better access to markets, and households seeking extension and advisory services.

Regarding pest management technologies, higher probabilities of adoption are associated with better market access and the receipt of agricultural training. Lower probability of adoption is associated with households belonging to lower social caste groups, such as Dalits and Janajatis.

Regarding disease management technologies, the factors positively influencing adoption are greater household size, closer market access, and more frequent seeking of agricultural advice and agricultural visits.

Regarding irrigation management, adoption is positively associated with more formal schooling of the household head, affiliation with farmers' organizations, and participation in agricultural training and farm visits.

Finally, regarding climate resilient technologies, adoption is positively associated with households participating in agricultural training and farm visits and with female-headed households.

The process of diffusion is found to be complex. While more years of farming experience generally induce farmers to obtain more information from informal sources about improved technologies and practices, greater exposure to demonstrations or training and membership in farmers' groups or cooperatives induce information gathering from more formal sources.

By promoting improved technologies and practices, the KISAN project generally increased farm profits, primarily by raising revenues while keeping the production costs unchanged. However, bivariate probit IPW models, which address self-selection not only in project participation but also in crop choices, reveal that these effects vary considerably according to the crops grown. This underscores the possibility that different production technologies or practices matter for different crops.

Our findings provide important policy implications for promoting technology adoption and diffusion in the western parts of Nepal. Improving market access has been found to be an important pathway to promoting technology adoption and diffusion. Quick access to a market reduces transportation and transaction costs, facilitates the purchase of inputs, reduces production costs, increases farm profitability, and provides exposure to improved technologies. Therefore, efforts to improve transportation infrastructure, expand road networks, and establish market centers would translate into higher adoption rates of improved technologies.

The organization of agricultural training and farm visits has also been found to be positively associated with the adoption of improved farm practices. There is no doubt that farmers' participation in such programs will help in their capacity building and motivate them to replicate such technologies. However, for resource-poor farmers, it is very important to provide subsidies, and link them to the input and output markets. Our study has found that the households receiving seed subsidies and credit are likely to have higher adoption rates of some of the modern technologies. Thus, it is imperative that in addition to providing a wide exposure to field demonstrations, farm visits and agricultural training, farmers are supported with the required input packages to increase their adoption rate of improved technologies.

In several regression models, we have also found that households belonging to the Dalit and Janajati social castes had adopted a smaller number of technologies than upper caste households (Brahmin and Chhetry). The constraints that limit the adoption of technologies by these groups need to be further investigated.

References

Asfaw, S., Shiferaw, B., Simtowe, F., Lipper, L., 2012. Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. Food Policy 37(3), 283–95.

Austin, P. C., 2011. An introduction to propensity score methods for reducing the effects of confounding in observational studies. Multivariate Behavioral Research 46(3), 399–424.

Bandiera, O., Rasul, I., 2006. Social networks and technology adoption in northern Mozambique. Economic Journal 116(514), 869–902.

CBS (Central Bureau of Statistics). 2011. Nepal living standard survey. Kathmandu: Government of Nepal.

Conley, T. G., Udry, C. R., 2010. Learning about a new technology: Pineapple in Ghana. American Economic Review 100(1), 35–69.

Evenson, R. E., Gollin, D., 2003. Assessing the impact of the Green Revolution, 1960 to 2000. Science 300(5620): 758–62.

Feder, G., Just, R. E., Zilberman, D., 1985. Adoption of agricultural innovations in developing countries: a survey. Economic Development and Cultural Change 33(2), 255–98.

Feleke, S., Zegeye, T., 2006. Adoption of improved maize varieties in southern Ethiopia: factors and strategy options. Food Policy 31(5), 442–57.

Foster, A., Rosenzweig, M., 1995. Learning by doing and learning from others: Human capital and technical change in agriculture. Journal of Political Economy 103(6), 1176–1209.

Ghimire, R., Huang, W., 2015. Household wealth and adoption of improved maize varieties in Nepal: A double-hurdle approach. Food Security 7(6): 1321–35.

Ghimire, R., Huang, W., Shrestha, R. B., 2015. Factors affecting adoption of improved rice varieties among rural farm households in central Nepal. Rice Science 22(1): 35–43.

Gollin, D., 2010. Agricultural productivity and economic growth. Handbook of Agricultural Economics 4, 3825–66.

Imbens, G., Woolridge, J., 2009. Recent developments in the econometrics of program evaluation. Journal of Economic Literature 47(1), 5–86.

Isgin, T., Bilgic, A., Forster, D., Batte, M., 2008. Using count data models to determine the factors affecting farmers' quantity decisions of precision farming technology adoption. Computers and Electronics in Agriculture 62(2), 231–42.

JICA, 2010. Commercialization of Agriculture in Nepal. Available at: https://www.jica.go.jp/nepal/english/office/others/c8h0vm000001jmat-att/newsletter_64.pdf

Krishnan, P., Patnam, M., 2014. Neighbors and extension agents in Ethiopia: Who matters more for technology adoption? American Journal of Agricultural Economics 96(1), 308–27.

Langyintuo, A. S., Mungoma, C., 2008. The effect of household wealth on the adoption of improved maize varieties in Zambia. Food Policy 33(6), 550–59.

Marenya, P. P., Barrett, C. B., 2007. Household-level determinants of adoption of improved natural resources management practices among smallholder farmers in western Kenya. Food Policy 32(4), 515–36.

Mariano M. J., Villano, R., Fleming, E., 2012. Factors influencing farmers' adoption of modern rice technologies and good management practices in the Philippines. Agricultural Systems 110, 41–53.

Mason, N. M., Smale, M., 2013. Impacts of subsidized hybrid seed on indicators of economic well-being among smallholder maize growers in Zambia. Agricultural Economics 44(6), 659–70.

MoAD (Ministry of Agriculture Development). 2014. *Agriculture Development Strategy*. Kathmandu: Government of Nepal.

MoF (Ministry of Finance). 2015. *Economic Survey*. Kathmandu: Government of Nepal.

Noltze M., Schwarze, S., Qaim, M., 2012. Understanding the adoption of system technologies in smallholder agriculture: The system of rice intensification (SRI) in Timor Leste. Agricultural Systems 108, 64–73.

Pamuk, H., Qaim, E., Adekunle, A., 2014. Do decentralized innovation systems promote agricultural technology adoption? Experimental evidence from Africa. Food Policy 44, 227–36.

Paudel, P., Matsuoka, A., 2008. Factors influencing adoption of improved maize varieties in Nepal: A case study of Chitwan District. Australian Journal of Basic and Applied Sciences 2(4), 823–34.

Polson, R. A., Spencer D. S., 1991. The technology adoption process in subsistence agriculture: The case of cassava in southwestern Nigeria. Agricultural Systems 36(1), 65–78.

Ramirez O. A., Shultz, S. D., 2000. Poisson count models to explain the adoption of agricultural and natural resource management technologies by small farmers in Central American countries. Journal of Agricultural and Applied Economics 32(01):21-33.

Ransom, J. K., Paudyal, K., Adhikari, K. 2003. "Adoption of improved maize varieties in the hills of Nepal. Agricultural Economics 29(3), 299–305.

Takeshima, H., 2017. Custom-hired tractor services and returns to scale in smallholder agriculture: A production function approach. Agricultural Economics 48(3), 363–72.

Takeshima, H., Adhikari, R. P., Kaphle, B. D., Shivakoti, S., Kumar, A., 2016. Determinants of chemical fertilizer use in Nepal. IFPRI Discussion Paper 1507. Washington, DC: International Food Policy Research Institute.

Takeshima, H., Adhikari, R., Shivakoti, S., Kaphle, B. D., Kumar, A., 2017. Heterogeneous returns to chemical fertilizer at the intensive margins: Insights from Nepal. Food Policy 69, 97–109.

Teklewold, H., Kassie, M., Shiferaw, B., 2013. Adoption of multiple sustainable agricultural practices in rural Ethiopia. Journal of Agricultural Economics 64(3), 597–623.

Wooldridge, J., 2007. Inverse probability weighted estimation for general missing data problems. Journal of Econometrics 141(2), 1281–301.

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