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Do improved agricultural practices boost farm productivity? the evidence from Karnataka, India

Barun Deb Pal and Sunil Saroj*

International Food Policy Research Institute, South Asia Office, New Delhi-110012, India

Abstract This study intends to analyse the impact of improved agricultural practices (IAPs) on crop productivity and farmers' income. A sample of 991 farmers has been selected purposively from four districts of Karnataka, where 50% of them are treated with IAPs. We employed the endogenous switching regression (ESR) model and the propensity score matching (PSM) method to assess the impact of IAPs on farmer income and crop productivity. The findings show that farm income for the treatment group was 23% higher than for control farmers and crop productivity improved 22%.

Keywords Farm productivity, improved agricultural practices (IAP), Karnataka, endogenous switching regression (ESR), impact assessment

JEL classification Q12, Q54

1 Introduction

Karnataka is the seventh largest state in India in terms of geographical area and the fifth largest in terms of agricultural land. It is also the second largest rain-fed area in India, where agriculture depends mainly on the south-west monsoon. Over 60% of its population depends on agriculture for livelihood, and most are small and marginal farmers with landholdings of less than 2 hectares (ha) (Government of Karnataka 2011).

The average yield of major dryland crops in the rain-fed areas of the state ranges from 1 to 1.5 t/ha, which is two to five times less than those on research farms (Singh et al. 2009). Inappropriate soil, water and crop management practices are depleting soil nutrient reserves, degrading land resources further and as a result lowering crop productivity (GoK 2011). Micronutrient deficiencies – even more widespread than mostly focused macronutrients phosphorus (P) and potassium (K) – are apparently holding back the state's productivity potential (Wani et al. 2011).

The Indian Council of Agricultural Research (ICAR) conducted large-scale agronomic trials; these showed that under conditions of micronutrient deficiency the application of major nutrients alone does not give the expected results, and that applying micronutrients could increase the yields of cereals by 0.3-0.6 tons/ha and even more for vegetables (GoK, Ministry of Agriculture 2012).

In 2009-10, the GoK initiated the flagship Bhoochetana programme. It aimed to raise the average productivity of selected rain-fed crops by 20%, bring about soil test–based nutrient management with a major thrust on micronutrients and distribute inputs at 50% subsidy at the cluster village level. In its first phase (2009-12), Bhoochetana covered over 3.7 million ha of land and more than four million farmers. Productivity in various crops and districts improved from 23% to 66% and benefited farmers in the last four years of this project (ICRISAT 2013).

The state government commenced a second phase of Bhoochetana to include irrigated agriculture. And it launched the Bhoochetana Plus/Bhoo Samruddhi initiative to address system-level initiatives through the ICRISAT-led consortium and in partnership with the nine Consultative Group for International Agricultural Research (CGIAR) institutions working

*Corresponding author: s.saroj@cgiar.org

in India. The programme aims to increase crop productivity in dry land/rain-fed area by adopting improved technology (Direct Seeded Rice (DSR), improved seeds and integrated nutrient management), conduct soil tests and prepare soil test maps. This paper considers all the components together and terms these improved agricultural practices (IAP). The targets of this programme are to

- raise agricultural systems productivity by 20%;
- enhance average family income by 25%;
- establish pilots and innovation platforms for farmers, line departments, researchers and policymakers;
- reduce the vulnerability of farmers to climate change and market forces; and
- develop a strategy for sustainable eco-friendly production systems using selected system-level interventions.

The Bhoo Samruddhi programme was implemented in a phased manner (2012-13 to 2016-17). In the first phase, 2012-13 to 2016-17, four districts – Bijapur, Chikkamagalur, Raichur and Tumkur – were selected in four different agroclimatic zones. A target of 80,000 ha was set for the four 'sites of learning' in the pilot districts over a period of four years. As a part of its implementation process, CGIAR partner institutions and the Department of Agriculture (DoA) started demonstrations of new or improved technology for various crops in farmers' fields and recorded the performance, but the data does not tell us if the programme raised farmer incomes or if farmers adopted improved technologies beyond the demonstrated plot; instead, it provides information on plot-level performance in terms of increment in yield, the input use pattern of crops and the economic benefits of farmers.

Does the adoption of innovative technologies increase farmer income? If yes, what is the increase? The selected districts faced severe drought during the three consecutive years from 2014 to 2016; were the improved practices effective in coping with the losses due to drought? This study analyses the impact of IAP on crop productivity and farmers' income in the above-mentioned four districts in Karnataka.

2 Empirical framework

The decision to adopt IAPs may be determined by several characteristics of farmers, like landholding size, socioeconomic characteristics and their perception of the inherent features of the practices. Griliches (1957) uses a logistic function to estimate the adoption curve for a hybrid seed corn that is dependent on seed availability and the adoption rate of the hybrid. A firm's decision to produce and sell a hybrid in a region hinges on operational profitability, determined by the overall corn area and marketing costs. Farmers' education, machinery ownership, irrigation water supply, capacity-enhancement activities and profit-oriented behavior are the key determinants in enhancing adoption of certified seed technology (Mariano et al. 2012).

Noltze et al. (2012) find in Timor Leste that training participation and the availability of household labour increases the probability and intensity of adoption of system of rice intensification technologies. Wubeneh and Sanders (2006) identify that soil type, rainfall risks and farmers' perceptions of technology characteristics and access to information were associated with the adoption of new sorghum cultivars. Floyd et al. (2003) observe a positive impact of farmers' extension on the adoption of new technologies. Ransom et al. (2003) find irrigated fertile land, ethnic group, years of fertilizer use, off-farm income and contact with extension as important determinants for adoption of improved maize varieties in Nepal.

Several other studies find that gender, age, education, experience and farmers' perceptions of the technology are important (Knowler & Bradshaw 2007; Vitale et al. 2011; Baumgart Getz et al. 2012). Farm characteristics such as the landholding, location, soil properties, access to irrigation and the agroecological and socioeconomic conditions of the area where the farm is located have also been found to affect adoption (D'Emden et al. 2008; Gedikoglu & McCann 2012). These researchers typically selected a few potential independent variables for inclusion in their analysis based on prior theorizing and testing, usually via logistic (logit) or probit regression, to determine which variables correlate with adoption in some statistically significant sense (Feder et al. 1985). Numerous researchers have studied the impact of agricultural technology on poverty (Pinstrup-Andersen et al. 1976;

Hossain et al. 1994; Winters et al. 1998; de Janvry & Sadoulet 1992, 2001; Irz et al. 2001). According to them, new agricultural technology influences the poor directly by raising farm household income and indirectly by raising the employment and wage rates of functionally landless labourers and by lowering the price of food staples. These studies do not explicitly point to a causal effect of agricultural technology adoption on farm household well-being; in other words, they fail to establish an adequate counterfactual situation and identify the true causality of change.

To assess the impact of a new technology on poverty, a researcher should be able to assess the situation in counterfactual and non-counterfactual scenario and infer can be drawn and implemented as policy (Mendola 2007). To address this methodological gap, Mendola (2007) used cross-sectional household survey data of rural Bangladesh and isolated the causal effect of adopting high-yielding varieties of rice on poverty alleviation by using the PSM method. Assessing the impact of agricultural extension is difficult, especially in terms of dealing with attribution issues and linking cause and effect quantitatively (Purcell & Anderson 1997). Many infrastructural variables and other factors affect agricultural performance in complex and contradictory ways, and the benefits are difficult to quantify (Anderson 2007; Birkhaeuser et al. 1991). There is no baseline data, and all the contributing variables cannot be included in production equations; these are other problems (Davis et al. 2012).

The challenges to impact studies lie in establishing a viable counterfactual; attributing the impact to an intervention; and coping with long and unpredictable lag times (Alston & Pardey 2001; Salter & Martin 2001). Studies may be confounded also by endogeneity in programme placement and extension, farmer interactions, farmer-to-farmer information flow, selection bias and policies that affect various measures. To overcome these challenges, Davis et al. (2012) list various approaches: experimental approaches; longitudinal comparisons (or reflexive control) for participants; cross-sectional comparisons of participants versus non-participants; econometrics, such as the instrumental variable approach; and (5) quasi-experimental and non-experimental approaches, including propensity score matching (PSM) and covariate matching and the double-difference estimator (Davis & Nkonya 2008; Smale et al. 2008). These approaches have been used by many researchers.

This study uses farm income or net return per hectare (INR) from crop and crop productivity (quintal/ha) as outcome indicators. Farm income is measured as the difference between total revenue and total production cost. Total revenue is the product of price and quantity, whereas crop price is determined by the sale value. Production cost includes seeds, urea, diammonium phosphate (DAP), potash, manure, micronutrients, biofertilizer, labour cost, custom hiring and pesticides. Crop productivity or yield is the crop production divided by area under cultivation. We classify crops[1] into cereals, pulses, oilseeds and other crops. To account for selection bias from both observable and unobservable factors, we employ the PSM and ESR models to estimate the impact of IAPs on outcome variables. We also use a logit model to examine the impact of factors associated with a treatment group that had adopted IAPs.

2.1 Logit model

A logit model was estimated to identify the factors that influence treatment farmers to adopt IAPs. Since the dependent variable was a binary variable (farmers have adopted IAPs = 1, otherwise = 0) and the independent variables were a mix of quantitative variables, the multivariate logistic regression in equation (1) was used:

$$Y = \log\left[\frac{p}{1-p}\right] = \beta_0 + \sum \beta_i X_i\,, \qquad \ldots(1)$$

where p represents the probability that the farmers are adopting IAPs and β_0 is the regression coefficient estimated by the maximum likelihood method. The explanatory variables used in the model include age, household size, smartphone ownership, social caste, education, landholding, major crops, access to irrigated land, soil health card (SHC) ownership, bank account possession and livestock. The interpretation of coefficients is less straightforward in the logit than the ordinary least squares (OLS) model. Usually, a positive

[1] Our sample had bajra, castor, chickpeas, cotton, green gram, groundnut, jowar, maize, onion, paddy, pigeon pea, potato, ragi, sorghum, sugarcane and sunflower growing cultivators. We defined these crops into four broad categories for better analysis.

coefficient for an independent variable increases the probability of a household being upwardly mobile. However, the marginal effects of the explanatory variables on the probabilities are not equal to the coefficients. Further calculations were required to estimate the marginal effects of each explanatory variable. The marginal effect of a variable was computed using equation (2):

$$\frac{\delta_p(y)}{\delta X_i} = \beta X_i \times \frac{\exp[Z]}{\left[1+\exp\exp(z)\right]^2}, \qquad \ldots(2)$$

where Z is the sum of coefficients multiplied by the means of the respective variables plus the constant term.

2.2 Propensity score matching (PSM)

We use the PSM method to construct the counterfactual and reduce the problems arising from selection biases from the sample. The main purpose of using this method is to find a group of non-treated plots (non-beneficiary/control) similar to the treated plots (beneficiary) in all relevant observable characteristics; the only difference is that the treatment group adopts IAPs and the other does not. Using propensity scores, the average treatment effect (ATT) for the treatment group can be estimated. Using this approach, there are many methods to match the propensity scores of the treatment and control groups. Asymptotically, all matching methods should give the same results. However, in practice, there are trade-offs in terms of bias and efficiency with each method (Caliendo & Kopeinig 2008). In our case, we use the nearest neighbour matching (NNM), radius matching, bootstrapping and kernel-based matching methods.

The basic modality is to find the 'neighbours' value (propensity score) of non-treated plots, which is close to the values of treated plots. The main purpose of the propensity score estimation is to balance the observed distribution of covariates across the groups of treatment and control groups. The balancing test is normally required after matching to ascertain whether the differences in covariates in the two groups in the matched sample have been eliminated, in which case the matched comparison group can be considered a plausible counterfactual (Ali & Abdulai 2010). Although several versions of balancing tests exist in the literature, the most widely used is the standardized mean difference (bias) between treatment and control groups suggested by Rosenbaum and Rubin (1985). In principle, after matching, there should be no systematic differences in the distribution of covariates between the groups.

Let Di be an indicator of whether farmers are beneficiaries or non-beneficiaries. The potential productivity outcome of being a beneficiary, represented by i, for each farmers is defined as i (Di). The ATT is computed as:

$$\Delta_{\text{ATT}} = E(\Delta|D_i=1) = E[(|\tau(1)|D_i=1] - E[\tau(0)|D_i=1], \qquad \ldots(3)$$

where Δ_{ATT} is the average treatment effect on the treated; $E[(|\tau(1)|D_i=1]$ is the expected outcome variable of beneficiary farmers; and $E[\tau(0)|D_i=1]$ is the expected outcome variable of beneficiary farmers if their land had not been demonstrated. The PSM method requires imposing conditional independence and common support assumptions for identification (Heckman et al. 1997). If these two assumptions are met, the PSM estimator for Δ_{ATT} is given as:

$$\Delta\frac{\text{PSM}}{\text{ATT}} = E_{p(X)|D_i=1}\left\{E\left[(\tau(1)\,|\,D_i=1, p(X)\right] - E\left[(\tau(0)\,|\,D_i=1, p(X)\right]\right\} \qquad \ldots(4)$$

We estimate propensity scores using a logit model. Following Heckman et al. (1997), we include only explanatory variables that influence beneficiary farmers and the outcome. We use the kernel matching algorithm for our main discussion, which uses the weighted averages of all subjects in the comparison group to construct the counterfactual (Caliendo & Kopeinig 2008). However, we probe the model's robustness using alternative matching methods as mentioned above. The PSM estimators do not account for selection on unobservable factors. Hence, we believe such selection bias had little impact on our results.

2.3 Endogenous switching regression (ESR) model

To check the robustness and accounting for selection bias, we also employ the ESR model. In contrast, the non-randomness of selection of IAPs may cause an econometric issue (i.e., heterogeneity of the impacts of IAPs). The standard econometric method of using a pooled sample of treatment and control groups (i.e., binary variable is used to assess the effect of IAPs on outcome indicators) might be inappropriate, as it assumes that the set of covariates has the same impact on treatment and control groups. To deal with this issue, we employ an ESR framework. We specify the selection equation for beneficiary farmers as:

$$M_i^* = X_i\alpha + \delta_i \text{ with } M_i = \begin{cases} 1 \text{ if } M_i^* > 0 \\ 0 \text{ otherwise} \end{cases} \quad \ldots(5)$$

Here, X is a vector of variables that determine farmer characteristics. These variables include age, household size, education, smartphone ownership, social structure, education, land size, growing of major crops, irrigated land, SHC ownership, livestock and bank account possession. In the second step, based on the results of the selection function, two regime equations are specified explaining the outcomes of interest: yield and net return from crop. The relationship between a vector of explanatory variables X and the outcome Y can be represented by $Y = f(X)$. Specifically, the two regimes are represented as follows:

Regime 1: $Y_{1i} = X_{1i}\beta_1 + \varepsilon_{1i}$ if $M_i = 1$

Regime 2: $Y_{2i} = X_{2i}\beta_2 + \varepsilon_{2i}$ if $M_i = 0$, …(6)

where Y_i is the outcome of interest (i.e., yield and net return from crop) in regimes 1 and 2, and X_i represents a vector of the explanatory variables discussed above. Finally, the error terms are assumed to have a trivariate normal distribution, with zero mean and covariance matrix. If the estimated covariance between δ and ε's (ρ_1 and ρ_2, respectively) are statistically significant, then the beneficiary farmers and the farm productivity are correlated. The estimated covariance, and , are the transformation of the correlation between the errors from the equation 6. Using this method, we found evidence of endogenous switching and rejected the null hypothesis that sample selectivity bias was absent. This model is defined as a 'switching regression model with endogenous switching' (Maddala & Nelson 1975).

We also calculate the farmers' conditional expectations for net return and yield in the four cases presented below (see also Table 1):

a. $E(Y_{1i}|M_i = 1) = [\Sigma_{Mi=1}(X_{1i}\beta_1 + s_{1n}\gamma_{1i})]/N_1$ …(7)

b. $E(Y_{2i}|M_i = 0) = [\Sigma_{Mi=0}(X_{2i}\beta_2 + s_{2n}\gamma_{2i})]/N_0$ …(8)

c. $E(Y_{2i}|M_i = 1) = [\Sigma_{Mi=1}(X_{1i}\beta_2 + s_{2n}\gamma_{1i})]/N_1$ …(9)

d. $E(Y_{1i}|M_i = 0) = [\Sigma_{Mi=0}(X_{2i}\beta_1 + s_{1n}\gamma_{2i})]/N_0$, …(10)

where and are the number of observations with and , respectively.

3 Data and sampling

In 2017, between June and August, we conducted a primary survey of beneficiary and non-beneficiary farmers in four districts listed under Phase I of the Bhoo Samruddhi program: Chikmagalur (166), Raichur (200), Tumkur (345) and Vijaypura (280). A sample of 22 talukas were selected purposively from the four districts chosen in consultation with CGIAR partner organizations and officials of the district DoA. A sample of 991 farmer households was selected for this study; 471 of these are beneficiary farmers and 520 are non-beneficiary farmers. Beneficiary farmers were selected randomly from the list obtained from ICRISAT. The non-beneficiary farmers were selected purposively from the same village with the criterion that for each beneficiary farmer in a village, there will be at least one non-beneficiary farmer who is cultivating the same crop for which technology was demonstrated in the beneficiary farmer's plot. The details of sample size and their distribution across beneficiary and non-

Table 1. Treatment and heterogeneity effect—Decision stage

Transitional heterogeneity	Decision stage		Treatment effects
	Treatment	Control	
Treatment	(a) $E(Y_{1i}\|M_i = 1)$	(c) $E(Y_{2i}\|M_i = 1)$	TT
Control	(d) $E(Y_{1i}\|M_i = 0)$	(b) $E(Y_{2i}\|M_i = 0)$	TU
Heterogeneity effects	BH[1]	BH[2]	TH

Note: Cases (a) and (b) in Table 1 represent the actual expectations observed in the sample. Cases (c) and (d) represent the counterfactual expected outcomes. However, following Heckman et al. (2001), we calculated the effect of the treatment "beneficiary" on the treated (TT) as the difference between (a) and (c), which represents the impact of IAPs on the outcome variable of the beneficiary farmers. Similarly, we calculated the difference between (d) and (b) as the effect of the treatment on the untreated (TU) for the farmers that did not were part of beneficiary members.

Table 2. District-wise sample size selected for this study

Name of the districts	No. of talukas selected for survey	No. of beneficiary farmer households	No. of non-beneficiary farmer households	Total
Raichur	5	107	93	200
Tumkur	7	156	189	345
Chikmagalur	4	72	94	166
Vijaypura	6	137	144	281
Total	22	471	520	991

beneficiary farmers are given in Table 2 and their location is given in Figure 1.

3.1 Characteristics of sample farmers

The data obtained through the primary survey covered a wide range of information on household characteristics, landholding, cropping patterns, economics of crop cultivation, adoption of IAPs, soil nutrient management and extension and knowledge dissemination. Table 3 presents summary statistics of variables used in an empirical model, along with the difference (using two sample t-tests) in each explanatory variable for treatment (beneficiary) and control (non-beneficiary) groups.

The interpretation of explanatory variables is straightforward. About 92% of the sample comprises male-headed households, and average age is about 50 years. The household heads have at least 27 years of experience in farming. In the sample, having a smartphone with an internet connection is the key variable. About 8% of the treatment group has a smartphone; while small, the figure is significantly

Figure 1: Sample districts in Karnataka

Table 3. Descriptive statistics of key variables

Variables	Beneficiary (N = 471)	Non-beneficiary (N = 520)	Difference in means (t-test)(beneficiary-non-beneficiary)	All (N = 991)
Socio-demographic variables				
Male-headed households (%)	93.42	91.33	2.09	92.32
Age of head of households (years)	50.45	50.81	-0.36	50.64
Age of head of households, squared (years)	2,699.70	2,741.00	-41.24	2,721.30
Experience in farming (years)	27.33	28.34	-1.01	27.86
Experience in farming, squared (years)	921.30	977.50	-56.21	950.70
Have smartphone with Internet connection (%)	8.07	4.42	3.64*	6.16
Social structure by caste (%)				
Scheduled Caste and Scheduled Tribes	23.35	30.38	-7.03**	27.04
Other Backward Caste	53.08	48.85	4.23	50.86
General	23.57	20.77	2.80	22.10
Education level of the head of household (%)				
Illiterate	31.85	38.85	-7.00*	35.52
Up to primary	22.93	21.92	1.01	22.40
Secondary	21.87	24.42	-2.55	23.21
Sr. sec. & above	23.35	14.81	8.55***	18.87
Household size (number)	5.26	5.03	0.24	5.14
Household size, squared (number)	33.03	30.21	2.82	31.55
Structure of farms (%)				
Marginal (< 1 ha)	66.83	53.98	12.85***	61.03
Small (1–2 ha)	18.88	27.69	-8.81***	22.86
Medium (2–4 ha)	11.33	15.54	-4.21*	13.23
Large (> 4 ha)	2.96	2.79	0.17	2.88
Average landholding (ha)	1.07	1.28	-0.21***	1.16
Major crops (%)				
Cereals	30.21	39.84	-9.63***	34.56
Pulses	39.74	28.88	10.85***	34.83
Oilseeds	29.56	27.49	2.07	28.62
Others	0.49	3.79	-3.29***	1.98
Economics of crop cultivation: Cost (INR/ha and USD/ha)				
Seed	1,849.30	2,029.20	-179.89	1,930.60
	[28.45]	[31.22]	[2.77]	[29.70]
Urea	282.20	288.50	-6.26	285.10
	[4.34]	[4.44]	[-0.10]	[4.39]
DAP	1,950.00	1,549.70	400.32***	1,769.10
	[30.0]	[23.84]	[6.16]	[27.22]
Potash	122.80	70.91	51.87**	99.34
	[1.89]	[1.09]	[0.80]	[1.53]
Manure	1,256.20	974.90	281.32*	1,129.10
	[19.33]	[15.00]	[4.33]	[17.37]
Micronutrients	0.39	0.22	0.17	0.32
	[0.01]	[0.01]	[0.01]	[0.01]

Contd...

Biofertilizer	111.90	164.90	-53.03	135.80
	[1.72]	[2.54]	[-0.82]	[2.09]
Labor	3,940.40	2,938.60	1,001.72***	3,487.70
	[60.62]	[45.21]	[15.41]	[53.66]
Tractor rent / custom hiring	1,831.70	1,507.10	324.62**	1,685.10
	[28.18]	[23.19]	[4.99]	[25.92]
Pesticides	207.70	158.90	48.83	185.60
	[3.20]	[2.44]	[0.75]	[2.86]
Total cost of cultivation	11,552.50	9,682.40	1,870.13***	10,707.50
	[177.73]	[148.96]	[28.77]	[164.73]
Total revenue per hectare (INR)	41,441.90	33,970.50	7,471.42**	38,066.00
	[637.57]	[522.62]	[114.94]	[585.63]
Net return / profit per hectare (INR)	29,889.40	24,288.20	5,601.29**	27,358.50
	[459.84]	[373.66]	[86.17]	[420.90]
Average production (quintal/hectare)	13.94	11.42	2.53**	12.80
Other details				
Access to irrigation (%)	33.97	20.62	13.35***	26.97
Have soil health card (%)	16.63	5.97	10.66***	11.03
Have bank account (%)	33.40	26.92	6.48**	30.00
Have livestock (%)	73.25	64.42	8.83**	68.62
District sample (%)				
Chikmagalur	15.29	18.08	-2.79	16.75
Raichur	22.72	17.88	4.84	20.18
Tumkur	33.12	36.35	-3.23	34.81
Vijaypura	28.87	27.69	1.18	28.25

Source: Authors' calculations based on International Food Policy Research Institute-Government of Karnataka (IFPRI-GoK) Survey, 2017
Note: USD values are given in square brackets. The conversion rate is USD 1 = INR 65.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

higher than the control group. Smartphones and mobile phones can act as catalysts to improve farm productivity and provide timely information (Mittal & Tripathi 2009).

More than 50% of the sample are from the Other Backward Castes (OBCs),[2] and about 20% of the sample are from the General Caste category, which comprises 75% of the total sample. The rest of the farmers (27%) are from Scheduled Castes (SCs) and Scheduled Tribes (STs).[3] In the case of education, about 35% of the farmers are illiterate, and 42% had achieved at least a secondary education. Among the control group–farmers, 38% are illiterate, which is significantly higher (7%) than the treatment group. In the treatment group, 23% of farmers have higher education, which is statistically significantly higher than the control group (8.5%). The average household size in the sample is about five. The average landholding is 1.16 ha, and the control group had significantly more in landholding (1.28 ha) than the treatment group (1.06 ha). In our sample, we found cereals (34.5%), pulses (34.8%) and oilseeds (28.6%) to be the major crops. About 39.8% of farmers from control group cultivate cereals – significantly higher, by 9.6%, than the treatment group. However, the treatment group had 10.8% more significant growth of pulses compared to the control group. Among oilseed growers, we did not find any statistical difference between the groups.

[2] Other Backward Castes is a collective term used by the Government of India to classify castes that are socially and educationally disadvantaged. It is one of several official classifications of the population of India, along with SCs and STs.
[3] Scheduled Castes and Scheduled Tribes are officially regarded as sociologically and economically backward people in India.

We have calculated the economics of crop cultivation using INR (Indian rupee) per hectare and USD per hectare as units of reporting. We captured all input costs like seeds, urea, diammonium phosphate (DAP),[4] potash, manure, micronutrients, biofertilizer, labour, custom hiring and pesticides. The total cost of cultivation in a year for the treatment group is INR 11,552 (USD 177.73) per hectare; for the control group, it is INR 9,682 (USD 148.96) per hectare. This shows a statistically significant difference of INR 1,870 (USD 28.77) between treatment and control group of farmers.

This positive difference (input cost of treatment group minus input cost of control group) is primarily because of the greater importance given to productive labour cost and the use of custom hiring services, which led to an increase in productivity. We have also observed that the treatment group spent more money on DAP, potash and manure. The revenue of the treatment group (INR 41,441; USD 637.57) was INR 7,471 (USD 114.94) more than that of the control group (INR 33,970; USD 522.62). Again, we have observed that the treatment group (INR 29,889; USD 459.84) earns higher income by INR 5,601 (USD 86.17) with respect to the control group (INR 24,288; USD 373.66). The average farm income from crop farming is about INR 27,358 (USD 420.90).

On the other hand, when we look at crop productivity, the average sample crop yield of all farmers is 12.8 quintal per hectare (q/ha), and the treatment group (13.9 q/ha) has a significantly higher yield (2.53 q/ha) than the control group (11.4 q/ha). The treatment group's yield is higher due primarily to the implementation of IAPs, productive labour involvement and the use of custom hiring. Access to an irrigation facility in our sample area is about 26.9%, and the difference between the treatment group (33.9%) and control group (20.6%) is statistically significant at 13.4%. This corroborates the fact that in the developing world irrigated crop yields are always higher than in their rain-fed counterparts (Hussain & Hanjra 2004; Lipton et al. 2005; Rosegrant & Perez 1997; Ringler et al. 2000).

The Soil Health Card (SHC)[5] is also an instrumental variable for the treatment group. On an average, about 11% of the sample farmers have an SHC – 16.6% of the treatment group and 5.9% of the control group, a statistically significant difference. About 30% of the sample farmers have an operational bank account, and the difference between the treatment (33.4%) and control group (26.9%) is statistically significant at 6.5%. In our sample, treatment group–farmers get a direct input subsidy on seeds, and money was directly transferred into their bank accounts. We have also found that having livestock is an important tool for the farmers. About 68.6% of the sample had livestock with them – 73.2% of the treatment group and 64.4% of the control group, a statistically significant difference of 8.8%.

4 Results and discussions

This section explains the parametric analysis obtained from the logit model, PSM and ESR methods. In all the models we include, district fixed effects and standard errors are clustered at the block level. The parameters are estimated at the plot level. As mentioned in the data and methodology section above, we have two outcome variables: farm income and crop productivity.

4.1 Estimates from logit model

Table 4 reports the parameter estimates for the factors affecting the treatment group's adoption of IAPs. The results reveal that the OBC and General Caste groups are more likely than SCs and STs to adopt the IAPs. For instance, the probability (marginal effect) of the adoption of IAPs would increase by 9.8% for OBCs and 12.6% for the General Caste. In terms of education, better educated farmers are more likely than illiterate farmers to adopt IAPs. The marginal effect of better educated farmers is 15.9%.

To check the real effect of landholding, we have taken its square as a covariate in the model. The square of landholding suggests that as the land size increases (3.1%) farmers are more likely to adopt IAPs. Farmers cultivating pulses (20.6%) and oilseeds (13.7%) have a higher probability than cereal-growing farmers of adopting IAPs. We found a negative association in the

[4] Diammonium phosphate (DAP) is a water-soluble ammonium phosphate salt widely used as a phosphorus fertilizer.

[5] In February 2015, the Government of India launched a scheme to issue farmers a Soil Health Card. It recommends the nutrients and fertilizers required for crops on individual farms. This scheme aims to help farmers use inputs judiciously and improve productivity.

Table 4. Determinants of beneficiary farmers using logit model

Variables	Logit coefficient	Marginal effect dy/dx
Age of head of household (years)	0.026	0.006
	(0.029)	(0.006)
Age of head of household, squared (years)	-0.000	-0.000
	(0.000)	(0.000)
Household size (number)	0.115	0.024
	(0.122)	(0.026)
Household size, squared (number)	-0.005	-0.001
	(0.009)	(0.002)
Have smartphone (%)	0.396	0.084
	(0.376)	(0.080)
Caste category (Base: SC & ST)		
Other Backward Caste (1 = Yes, 0 = Otherwise)	0.458**	0.098**
	(0.208)	(0.045)
General (1 = Yes, 0 = Otherwise)	0.587***	0.126***
	(0.199)	(0.044)
Education category (Base: Illiterate)		
Up to primary (1 = Yes, 0 = Otherwise)	0.056	0.012
	(0.208)	(0.044)
Secondary (1 = Yes, 0 = Otherwise)	0.141	0.030
	(0.172)	(0.037)
Sr. sec. & above (1 = Yes, 0 = Otherwise)	0.743***	0.159***
	(0.230)	(0.049)
Average landholding (hectare)	-1.108***	-0.236***
	(0.222)	(0.046)
Average landholding, squared (hectare)	0.146***	0.031***
	(0.040)	(0.008)
Crops growing households (Base: Cereals)		
Pulses (1 = Yes, 0 = Otherwise)	0.968**	0.206***
	(0.378)	(0.078)
Oilseeds (1 = Yes, 0 = Otherwise)	0.641***	0.137***
	(0.229)	(0.047)
Others (1 = Yes, 0 = Otherwise)	-1.659**	-0.354**
	(0.658)	(0.142)
Irrigated land (%)	0.423**	0.090**
	(0.201)	(0.043)
Have soil health card (%)	1.006**	0.215***
	(0.391)	(0.082)
Have livestock (%)	0.206	0.044
	(0.156)	(0.033)
Have bank account (%)	0.288	0.062
	(0.186)	(0.039)
District fixed effects	Yes	
Constant	-1.990**	
	(0.843)	
Observations	1,110	1,110

Source: Authors' calculation from IFPRI-GoK Survey, 2017.
Note: Robust standard errors are given in parentheses. *** $p < 0.01$, ** $p < 0.05$.

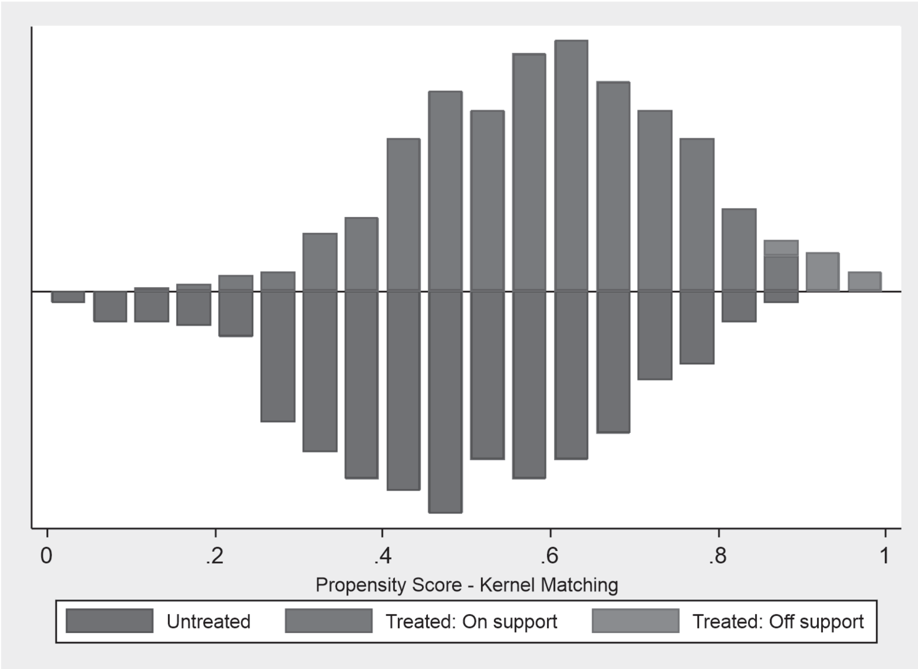

Figure 2. Common support

case of other crops. This may be attributed to lower frequency distributions of other crop-growing farmers. Having access to an irrigation facility and SHC are also key variables for the farmer regarding the adoption of IAPs. The probability of adoption of IAPs would increase by 9% in the case of access to irrigation and by 21% in the case of an SHC.

4.2 Propensity score matching (PSM) estimates

We used a logit model to match covariates, but we did not mention the estimates obtained from logit, which are equal to the above-mentioned estimates in table 4. Here we focus on the matching process and common support technique, and the next section will discuss ATT. In Figure 2, the distribution of propensity scores suggests that the common support condition is satisfied, as we can observe that there is a substantial overlap in the distribution of the propensity scores of both treated and non-treated groups. The upper half refers to the propensity score distribution of treated individuals, and the bottom half refers to the control group.

Table 5 represents the covariate balancing tests before and after matching using the nearest neighbourhood method. The values represent a substantial reduction in biasedness after the matching techniques. The *p* value of the likelihood ratio indicates that the joint significance of covariates was rejected after matching, whereas it was not rejected in unmatched cases (before matching). This helps to balance the distribution of covariates between both groups, rather than obtaining a precise prediction of selection into treatment.

4.2.1 Treatment effect on farm income

Table 6 estimates the ATT estimated by kernel matching, NNM, radius and bootstrapping. The estimates reveal that the treatment group had higher farm income compared to the control group. In all the matching estimates, the ATTs range from INR 4,906 per hectare to INR 6,531 per hectare. The result is consistent and close to our original estimates (Table 3). From the matching techniques, about 21–31 observations were off support,[6] which is reflected in Figure 2. The impact of IAPs is clearly observed for the treatment group, which has a higher income by INR 6,531 per hectare (NNM = 3) compared to the control group.

4.2.2 Treatment effect on crop yield

Following the same methods replicated in farm income, the estimates in Table 7 reveal that the treatment group

[6] Lying outside the region of common support.

Table 5. T-test for equality of means of each variable before and after the match

Variable	Matched	Treated	Control	% Bias	% Reduction in bias	t	p > t
Age of head of household (years)	U	50.15	50.57	-3.30		-0.55	0.58
	M	50.02	49.83	1.50	55.70	0.26	0.80
Age of head of household, squared (years)	U	2,674.40	2,720.10	-3.50		-0.59	0.56
	M	2,662.90	2,638.90	1.90	47.60	0.32	0.75
Household size (number)	U	5.32	5.07	11.10		1.83	0.07
	M	5.25	5.18	3.20	70.90	0.56	0.58
Household size, squared (number)	U	33.91	30.49	9.80		1.61	0.11
	M	32.53	31.92	1.70	82.20	0.31	0.76
Have smartphone with Internet connection (%)	U	0.08	0.05	14.00		2.29	0.02
	M	0.07	0.09	-4.30	69.40	-0.67	0.51
Caste category							
Scheduled castes and Scheduled tribes	U	0.24	0.30	1.60		0.26	0.79
	M	0.24	0.31	3.20	-101.90	0.54	0.59
Other backward caste	U	0.53	0.48	10.20		1.70	0.09
	M	0.53	0.54	-2.40	76.40	-0.42	0.68
General	U	0.23	0.22	3.90		0.65	0.52
	M	0.23	0.25	-4.20	-6.30	-0.70	0.48
Education category							
Illiterate	U	0.32	0.39	-14.50		-2.41	0.02
	M	0.33	0.32	2.90	80.00	0.50	0.62
Up to primary	U	0.22	0.24	-4.00		-0.66	0.51
	M	0.23	0.24	-3.70	6.40	-0.63	0.53
Secondary	U	0.21	0.23	-3.20		-0.53	0.60
	M	0.22	0.22	-1.90	41.30	-0.32	0.75
Sr. sec. & above	U	0.25	0.15	25.00		4.10	0.00
	M	0.24	0.22	3.40	86.40	0.55	0.58
Average landholding (hectare)	U	1.06	1.28	-21.30		-3.53	0.00
	M	1.08	1.09	-1.40	93.50	-0.24	0.81
Average landholding, squared (hectare)	U	2.09	2.63	-9.60		-1.61	0.11
	M	2.14	2.13	0.20	98.00	0.03	0.98
Crops grown							
Cereals	U	0.30	0.40	-20.20		-3.35	0.00
	M	0.31	0.31	-0.20	99.20	-0.03	0.98
Pulses	U	0.40	0.29	23.10		3.82	0.00
	M	0.39	0.39	-0.80	96.50	-0.13	0.89
Oilseeds	U	0.29	0.27	4.30		0.72	0.47
	M	0.30	0.31	-2.10	52.20	-0.35	0.73
Others	U	0.00	0.04	-22.90		-3.94	0.00
	M	0.01	0.00	2.00	91.30	0.81	0.42
Irrigated land (%)	U	0.33	0.23	23.30		3.85	0.00
	M	0.31	0.31	0.90	96.20	0.15	0.88

Cond...

Have soil health card (%)	U	0.16	0.07	28.50		4.64	0.00
	M	0.14	0.15	-4.00	86.00	-0.61	0.54
Have livestock (%)	U	0.75	0.67	17.10		2.84	0.01
	M	0.74	0.73	1.30	92.30	0.23	0.82
Have bank account (%)	U	0.35	0.29	13.30		2.20	0.03
	M	0.34	0.33	2.60	80.70	0.43	0.67
Districts							
Chikmagalur	U	0.16	0.20	-10.70		-1.79	0.07
	M	0.16	0.14	6.50	39.60	1.18	0.24
Raichur	U	0.24	0.21	6.50		1.08	0.28
	M	0.24	0.22	3.70	43.10	0.63	0.53
Tumkur	U	0.31	0.28	6.40		1.06	0.29
	M	0.31	0.31	0.10	99.00	0.01	0.99
Vijaypura	U	0.29	0.31	-3.40		-0.57	0.57
	M	0.29	0.32	-4.80	-39.20	-0.81	0.42

Source: Authors' calculations from IFPRI-GoK Survey, 2017
Note: U = unmatched samples; M = matched samples.

Table 6. Robustness of the ATT estimates for different algorithm estimators of farm income

Matching algorithm	Observations on the common support		Off support	ATT per hectare (in INR and USD)	Standard error
	Treatment	Control			
Kernel matching					
Bandwidth (0.01)	577	502	31	5,355.70** [82.40]	(2,947.97)
Bandwidth (0.05)	587	502	21	5,054.10** [77.76]	(2,874.19)
Nearest neighborhood					
N = 1	587	502	21	5,757.12** [88.57]	(3,624.52)
N = 3	587	502	21	6,531.12** [100.48]	(3,214.33)
N = 5	587	502	21	5,796.51** [89.18]	(2,902.63)
Radius					
Caliper =.01	577	502	31	5,287.27** [81.34]	(2,931.93)
Caliper =.05	587	502	21	4,906.83** [75.49]	(2,866.06)
Bootstrap					
Replication = 50	N.A.	N.A.	N.A.	5,006.47** [77.02]	(2,573.59)
Replication = 100	N.A.	N.A.	N.A.	5,018.35** [77.21]	(2,877.67)

Source: Authors' calculations from IFPRI-GoK Survey, 2017
Note: Standard errors are given in parentheses. USD values are given in square brackets. The conversion rate is 1 USD = INR 65.
** $p < 0.05$.

Table 7. Robustness of the ATT estimates for different algorithm estimators of yield

Matching algorithm	Observations on the common support Treatment	Control	Off support	ATT per hectare	Standard error
Kernel matching					
Bandwidth (0.01)	577	502	31	2.67**	(1.35)
Bandwidth (0.05)	587	502	21	2.74**	(1.32)
Nearest neighborhood					
N = 1	587	502	21	2.17**	(1.78)
N = 2	587	502	21	2.58**	(1.56)
N = 5	587	502	21	3.27***	(1.39)
Radius					
Caliper =.01	577	502	31	2.56**	(1.35)
Caliper =.05	587	502	21	2.64**	(1.32)
Bootstrap					
Replication = 50	N.A.	N.A.	N.A.	2.68***	(1.20)
Replication = 100	N.A.	N.A.	N.A.	2.68***	(1.16)

Source: Authors' calculations from IFPRI-GoK Survey, 2017
Note: Standard errors are given in parentheses.
*** $p < 0.01$, ** $p < 0.05$.

had higher crop productivity, or yield, as compared to the control group. In all the matching estimates, the ATTs range from 2.17 to 3.27 quintal per hectare. The result is consistent, and close to our original estimates (Table 3). From the matching techniques, about 21–31 observations were off support, which is reflected in Figure 2. The impact of IAPs is clearly observed for the treatment group, which has a higher yield by 2.58 quintal per hectare (NNM = 3) compared to the control group.

4.3 Results from ESR model

4.3.1 Estimates of farm income

The results of the participation equation given in the third column of Table 8 suggest that positive drivers of IAP adoption among farmers include higher education, large landholding (square of landholding), pulses and oilseed cultivation, access to irrigation, SHC ownership and bank account possession. In the OLS model (column 4) we found a positive coefficient for the treatment group on farm income, but it was not significant. The OLS approach assumes that adoption of IAPs is exogenously determined, even though such adoption is endogenously determined. Therefore, using the OLS approach here will lead to biased and inconsistent estimates. To correct for these weaknesses, the results presented in first and second columns of Table 8 provide estimates for endogenous switching in the farm income function.

The estimated coefficient of correlation () is not statistically significant in either function. This finding suggests that we failed to reject the null hypothesis that sample selectivity bias was absent in both equations. Nevertheless, we found a difference between the coefficient of the farm income function in the treatment group and its counterparts, indicating the presence of heterogeneity in the sample. Farm income is significantly higher for the treatment group than for the control group.

Higher education and access to irrigation had a positive effect on farm income for the control group, but oilseed and other crop growers had a negative effect. However, for the treatment group, upper castes (OBC and general caste), higher education, access to irrigation and bank account possession had a positive effect on farm income. Those with higher education had a higher income because higher education enhances the capacity to adapt to new improved practices (Adeoti 2009). The oilseed cultivators from the treatment group had a

Table 8. Estimates of farm income using ESR Model

	1 Treatment = 1 (farmers in treatment group)	2 Treatment = 0 (farmers in control group)	3 Treatment = 1, Otherwise = 0	4 OLS
Dependent variable →	Farm income	Farm income	Group	Farm income
Group^				2,397.712 (2,983.330)
Age of head of household (years)	-131.433 (489.778)	-80.784 (818.309)	0.016 (0.017)	121.452 (386.478)
Age of head of household, squared (years)	3.060 (5.387)	-1.290 (7.065)	-0.000 (0.000)	-0.453 (3.549)
Household size (number)	1,511.910 (2,916.231)	-1,783.470 (1,352.589)	0.091 (0.071)	368.072 (1,607.632)
Household size, squared (number)	-163.850 (172.910)	50.178 (78.207)	-0.004 (0.005)	-82.166 (104.682)
Have smartphone (%)	-9,741.216 (4,167.649)	4,402.138 (11,810.704)	0.172 (0.217)	-4,362.915 (4,679.052)
Caste category (Base: SC & ST)				
Other Backward Caste^	6,631.150** (2,634.999)	362.661 (4,964.981)	0.045 (0.142)	4,274.815 (3,757.931)
General^	15,937.561** (7,341.751)	-5,649.005 (5,526.389)	0.095 (0.122)	8,393.204 (4,894.366)
Education category (Base: Illiterate)				
Up to primary^	5,799.694 (3,880.031)	4,079.622 (2,913.035)	0.087 (0.134)	3,731.972 (2,966.577)
Secondary^	14,835.474** (6,726.728)	6,352.056 (4,247.939)	0.092 (0.104)	12,657.470*** (4,023.721)
Sr. sec. & above^	15,267.814* (9,120.214)	9,425.353** (3,746.390)	0.462*** (0.145)	14,760.767*** (4,566.616)
Average landholding (hectare)	-2,471.970 (4,499.100)	-2,196.012 (1,463.731)	-0.214*** (0.073)	-15,184.695** (6,049.405)
Average landholding, squared (hectare)	3,857.038 (8,026.129)	2,711.752 (5,574.339)	0.555*** (0.168)	2,426.786** (882.300)
Crops growing households (Base: Cereals)				
Pulses^	-478.007 (12,036.715)	-17,290.195 (11,135.831)	0.578*** (0.224)	-7,284.981 (8,331.293)
Oilseeds^	-22,091.427*** (6,035.714)	-21,151.045*** (7,834.630)	0.337** (0.133)	-20,756.897*** (5,202.567)
Others^	178,095.250 (159,307.880)	-28,633.213*** (9,420.773)	-0.998*** (0.336)	3,420.659 (30,683.552)
Access to irrigation^	11,932.855** (5,403.897)	10,488.047*** (4,011.955)	0.268** (0.128)	9,457.432** (4,132.528)
Have soil health card^	-271.176 (8,485.237)	-6,547.387 (5,694.766)	0.586** (0.235)	2,093.491 (8,186.229)
Have livestock^	-3,672.867 (4,428.108)	1,461.383 (4,110.284)	0.160 (0.100)	-1,609.766 (3,326.227)

Contd...

Have bank account^	5,638.377*	-374.278	0.181*	4,741.749*
	(2,941.733)	(2,908.144)	(0.104)	(2,317.416)
Constant	9,399.123	39,943.064	-1.313**	17,152.094
	(35,946.127)	(26,833.040)	(0.519)	(16,190.317)
Sigma (σ_i)	10.767***	10.408***		
	(0.015)	(0.005)		
Rho (ρ_j)	-0.087	0.027		
	(0.304)	(0.290)		
District fixed effects	Yes			Yes
Observations	1,110	1,110	1,110	1,110

Source: Authors' calculations from IFPRI-GoK Survey, 2017
Note: Robust standard errors are given in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ^denotes binary variable

negative effect on farm income as compared to cereals cultivators.

4.3.2 Estimates of yield

Similarly, we found the same pattern in the case of crop productivity or yield. The results of the participation equation given in the third column of Table 9 suggest that the positive drivers of IAP adoption include higher education, large landholding (square of landholding), pulses and oilseed cultivation, access to irrigation, have SHC ownership and bank account possession. In the OLS model (column 4) we found a positive, but not significant, coefficient for the treatment group on yield.

The estimated coefficient of correlation (ρ_j) is not statistically significant in either function and we found a difference between the coefficient (σ_i) of the yield function in the treatment group and its counterparts, indicating the presence of heterogeneity in the sample. The yield is significantly higher for the treatment group than for the control group.

Household size (squared term), farmers belonging to OBCs, higher education (secondary), access to irrigation and livestock rearing had a positive effect on yield for the control group. But oilseed cultivation had a negative effect on yield with respect to cereal-growing cultivators for the control group. In the case of the treatment group, higher education and access to irrigation had a positive effect on yield. Education improves the ability to face challenges by the farmers and thus improve productivity or yield (Adeoti 2009). Whereas pulse and oilseed growers had a negative coefficient for the yield function as compared to cereal-growing farmers.

4.3.3 Treatment effects of adoption of IAPs on farm income and yield

From the above estimations of the farm income and yield equation (obtained from the ESR model), the next step is to calculate the expected values. Table 10 presents the expected value of farmers' income and yield under actual and counterfactual conditions. Cells (a) and (b) represent the expected value of outcome variables. The expected values for farmers' income for the treatment group (INR 29,942.5; USD 460.65) was higher than for the control group (INR 25,965.2; USD 399.46). This simple comparison, however, could be misleading in attributing the different values of farm income to the treatment group. The last column of the first panel in Table 10 presents the treatment effects of the treatment group on farmers' income at the plot level. In the counterfactual case (c), farmers who are under treatment would have lower farm income by INR 3,977.3 (USD 61.19) if they had not been treated. The positive mean difference of (d) and (b) elicits a similar conclusion: control group–farmers would have increased the net return, or income, by INR 14,363.0 (USD 220.97) if they were in the treatment group. However, the transitional heterogeneity effect for farm income is negative, meaning that the effect would be greater for the control group than the treatment group. This could be because of large landholdings in the control group, from which a higher return of adoption of IAPs can be expected for non-treated groups.

Table 9. Estimates of yield using ESR model

	1 Treatment = 1 (farmers in treatment group)	2 Treatment = 0 (farmers in control group)	3 Treatment = 1, Otherwise = 0	4 OLS
Dependent variable →	Yield	Yield	Group	Yield
Group^				1.582 (1.464)
Age of head of household (years)	-0.133 (0.323)	-0.142 (0.272)	0.015 (0.017)	0.080 (0.212)
Age of head of household, squared (years)	0.002 (0.003)	0.001 (0.002)	-0.000 (0.000)	-0.000 (0.002)
Household size (number)	0.793 (0.997)	-1.807** (0.735)	0.093 (0.070)	-0.431 (0.411)
Household size squared (number)	-0.081 (0.059)	0.074** (0.038)	-0.005 (0.005)	-0.010 (0.032)
Have smartphone (%)	-3.491 (2.231)	-3.356 (4.467)	0.168 (0.219)	-2.760 (2.086)
Caste category (Base: SC & ST)				
Other Backward Caste^	1.756 (1.663)	5.023* (2.648)	0.043 (0.136)	4.233** (1.951)
General^	1.546 (1.846)	0.102 (1.980)	0.091 (0.120)	3.323* (1.637)
Education category (Base: Illiterate)				
Up to primary^	3.939** (1.934)	1.347 (1.563)	0.086 (0.136)	2.039 (1.415)
Secondary^	6.601* (3.523)	2.508* (1.512)	0.092 (0.105)	5.141** (2.451)
Sr. sec. & above^	2.906 (3.193)	2.932 (2.116)	0.458*** (0.139)	4.630** (2.225)
Average landholding (hectare)	-0.233 (1.159)	-0.446 (0.944)	-0.212*** (0.070)	-8.704*** (2.063)
Average landholding Squared (hectare)	5.756 (5.103)	1.211 (3.352)	0.560*** (0.160)	1.540*** (0.294)
Crops growing households (Base: Cereals)				
Pulses^	-13.901*** (3.837)	-7.583 (5.657)	0.583** (0.229)	-11.568** (4.543)
Oilseeds^	-16.613*** (3.346)	-8.555** (4.163)	0.337** (0.134)	-12.709*** (3.831)
Others^	-13.624 (9.798)	-5.496 (6.298)	-0.994*** (0.345)	4.357 (13.284)
Access to irrigation^	7.731** (3.693)	7.820*** (2.887)	0.273** (0.139)	7.382** (2.716)
Have soil health card^	-0.367 (4.708)	-4.122 (4.165)	0.584*** (0.225)	2.004 (2.880)
Have livestock^	0.854 (1.329)	2.199* (1.163)	0.161 (0.100)	0.585 (1.339)

Contd...

Have bank account^	2.554	-0.102	0.182*	2.294**
	(1.570)	(1.426)	(0.104)	(1.069)
Constant	17.426	28.253***	-1.306**	16.476*
	(16.592)	(10.414)	(0.520)	(8.504)
Sigma (σ_i)	2.828***	2.667***		
	(0.031)	(0.003)		
Rho (ρ_j)	-0.136	0.050		
	(0.547)	(0.409)		
District fixed effects	Yes			Yes
Observations	1,110	1,110	1,110	1,110

Source: Authors' calculations from IFPRI-GoK Survey, 2017.
Note: Robust standard errors are given in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. ^ denotes binary variable

Table 10. Treatment and heterogeneity effect

	Treatment	Control	Treatment effects
Net return (INR/ha)			
Treatment	(a) 2,9942.51	(c) 2,5965.22	TT = 3,977.29***
	[460.65]	[399.46]	[61.19]
Control	(d) 3,8651.17	(b) 2,4288.16	TU = 1,4363.01***
	[594.63]	[373.66]	[220.97]
Heterogeneity effects	BH_1 = -8,708.66	BH_2 = 1,677.06	TH = -10,385.70***
	[-133.98]	[25.80]	[-159.78]
Production (q/ha)			
Treatment	(a) 13.58	(c) 11.99	TT = 1.59***
Control	(d) 16.59	(b) 11.16	TU = 5.42***
Heterogeneity effects	BH_1 = -3.01	BH_2 = 0.83	TH = -3.83***

Source: Authors' calculations from IFPRI-GoK Survey, 2017
Note: USD values are given in square brackets. The conversion rate is 1 USD = INR 65.
*** p < 0.01.

Similarly, as described above, the impact of IAPs on yield for the treatment group (1.59 q/ha) is also positive and significant. Their mean yield was 13.3% higher than it would have been if they had not been treated. The positive mean difference of (b) and (d) indicates that the control group would have had higher yields by 5.4 q/ha if they had been treated.

5 Conclusion and policy recommendations

Low productivity in rain-fed agriculture, especially in semi-arid regions, threatens the livelihood of farmers; therefore, identifying technologies that can enhance crop yield and farmer income is a novel step taken by policymakers to ensure sustainable and inclusive growth. The Bhoo Samruddhi programme of the Government of Karnataka has benefited 60% of its farmers and enhanced the productivity of 10 million ha of agricultural land. To assess if improved technologies have been effective in increasing farmers' income and to find the key drivers of adoption, this study conducted a primary survey in the pilot districts (sites of learning) and collected data from around 1,000 farmer households. The empirical analysis adopted in this study is based at the plot level, and it employed semi-parametric and parametric econometric methods to strengthen our findings.

The results suggest that the impact of IAPs for the treatment group was positive compared to the control group for both outcome variables. Here, we have estimated farm income and yield using three different approaches – semi-parametric (INR 5,601.29 and 2.53 q/ha), PSM (INR 4,632.17 and 2.67 q/ha) and ESR

(INR 3,977.29 and 1.59 q/ha) – and found a positive significant influence. In terms of percentage change, the values range from 15% to 23% for farm income and from 13% to 22% for yield. This study also found that level of education, size of holding access to irrigation and SHC are the key drivers of the adoption of IAPs in the study area.

During the survey we found that the limited supply of seeds hinders the adoption of improved practices in the study area. Therefore, enabling access to improved seeds would be essential in scaling up the Bhoo Samruddhi programme across districts in the state. The state of Karnataka should consider strengthening the seed value chain; regular farmer training and capacity-building about the SHC; and R&D on climate-resilient farming systems.

A public private partnership model can be explored to strengthen the seed value chain and the supply of improved seeds. Seed production through a contract farming business model can benefit both farmers and distributors. The commercial production of biofertilizers would increase farmer incomes and promote nutrient management. Biofertilizer production using green waste reduces the open dumping of waste and environmental degradation and also reduces the demand for chemical fertilizers. A few farmers have started producing biofertilizers at the domestic level. Hence, commercialization can increase producer farmers' income and maintain soil health.

Regular farmer training and capacity-building about the SHC is necessary. Research and development on climate-resilient farming systems is necessary to consider improved technologies through the lenses of climate change adaptation and resilience building.

Karnataka is in a semi-arid region, and the government should focus on expanding irrigation facilities through innovative methods of water conservation. Investment in developing water conservation infrastructure will be essential. Research on technology innovation for on-farm water conservation can reduce the cost of irrigation investment.

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