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IMPACT OF AGRICULTURAL RELATED TECHNOLOGY ADOPTION ON POVERTY: A STUDY OF SELECT HOUSEHOLDS IN RURAL INDIA

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Abstract

This paper applies a program evaluation technique to assess the causal effect of adoption of agricultural related technologies on consumption expenditure and poverty measured by different indices. The paper is based on a cross-sectional household level data collected during 2014 from a sample of 270 households in rural India. Sensitivity analysis is conducted to test the robustness of the propensity score based results using the "rbounds test" and the mean absolute standardized bias between adopters and non-adopters. The analysis reveals robust, positive and significant impacts of agricultural related technologies adoption on per capita consumption expenditure and on poverty reduction for the sample households in rural India.

Keywords: *Agriculture related technology adoption, propensity score matching, poverty, Odisha, India*

JEL Codes: *C13, C15, O32, O38*

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INTRODUCTION

Growth in agricultural output is one of the most effective means to address poverty in the developing world. In this line of argument, the Department for International Development (2003) estimates that a one percent increases in agricultural productivity could reduce poverty between 0.6 and 2 percent. However, growing population is one of the major challenges in developing countries to increase agricultural productivity in a sustainable way, to meet the demand of the food security issues. The growth in production cannot come from area expansion but have to come from growth in yields emanating from scientific advances offered by biotechnology and other plant breeding initiatives (de-Janvry et al., 2001). In the increasing research of improved varieties of major crops that enhanced the productivity of agriculture, impact assessment studies were conducted to arrive at the direct and the indirect welfare impacts. Kijima et al., (2008) in Uganda conducted a study on the impact of rice, and found that rice adoption reduces poverty without deteriorating the income distribution. Similarly, Winters et al., (1998); Mwabu et al., (2006); and Wu et al., (2010) show positive impact of agricultural technologies adoptions. However, there are serious complexities associated with understanding the impact pathways through which agricultural technology adoption might affect household welfare. This is because crop production can affect household welfare both directly and indirectly. Consistent with this notion, de Janvry et al., (2001) reports that crop production affects poverty directly by raising welfare of poor farmers who adopt the technological innovation, through increased production for home consumption, higher gross revenues from sales, lower production costs, and lower yield risks. The indirect ways through which crop production affects welfare include the prices of food for net buyers and employment and wage effects in agriculture and related activities.

In a poor and backward state like Odisha in India, it is least expected that the development scenario of the village and the pace of socio-economic transformations could be better. The state has to make a longitudinal perspective plan for the transformation of the subsistence oriented backward agricultural economy in order to solve the problem of poverty and to improve the 'quality of life' of rural people. Dependence of population on primary sector occupations is quite high, whereas agriculture with its present state of infrastructure and technology and, above all, operational holdings is itself not in a position to provide a substantial form of gainful livelihood to the majority of rural population in Odisha. There have been little occupational diversifications of population at the village level. Irrigation infrastructure created through many development projects has failed to achieve desired goal across space and people. Often this serves the interest of only large, medium and semi-medium farmers. Like this, the welfare programmes and Minimum Needs Programme implemented by the state under social sector development to lessen poverty and improve the 'quality of life' of poor in rural areas hardly reach the targeted sections of population.

In a poor and backward state showing highest incidence of rural poverty, the development of hardcore backward districts requires special attention. It is found that the socio-economic conditions of people in the undivided Kalahandi, Bolangir and Koraput districts, popularly known as the KBK districts, have worsened over the years. These three districts have been affected by the '*backwash effects*' of development, which may probably be due to their inherent disadvantageous factors like poor quality of human capital, backward and unsustainable agriculture coupled with reckless exploitation of forest resources. This study is an attempt to see the impact of agricultural technology adoption on poverty of the select households of the Jeypore sub-division of the Koraput district of Odisha state.

The undivided Koraput district is characterized by certain features, historical, natural and geographical. The district lies on a section of the Eastern Ghat discontinuous range of mountains and holds five natural divisions, with a mean elevation of 3000, 2500, 2000, 1000 and 500 feet above sea level, respectively. The district has two parts, each characterized by a distinct type of rock; the 2000 feet plateau of Jeypore, with its much lower extension down into the Malkangiri subdivision (Malkangiri district), and the high hilly regions of the Eastern Ghat, lying between the Jeypore plateau and the Visakhapatnam coastal plains. This geographical setting has to a large extent isolated the region from the plain coastal districts of Odisha. Among the consequences of this, the region has been able to preserve much of its varied and prolific fauna and flora, and its aboriginal inhabitants have not undergone radical change as a result of contact with modern civilization. The location of this area, economic activities and socioeconomic profile gives us the motivation of studying the impact of the agricultural technology adoption and its impact on poverty at household level.

The role of agricultural technology and its impact on rural poverty and fostering overall economic development has been widely documented in the economic literature. Although quite complex, the relationship between the adoption of new technology and poverty reduction has been perceived to be positive (Bellon et al., 2006; Binswanger and von Braun, 1991; Evenson and Gollin, 2003; Just and Zilberman, 1988). Productivity-improving technologies reduce poverty by reducing food prices, facilitating the growth of nonfarm sectors, and by stimulating the transition from low productivity subsistence agriculture to a high productivity agro-industrial economy (Just and Zilberman, 1988). However, the potential for poverty reduction through reduced food prices, growth in the nonfarm sector and agricultural commercialization depends to a large extent on the magnitude of productivity gains in agriculture. However, the impact of agricultural technology adoption is necessary to understand at farm-household level. It is also important to distinguish between the direct and the indirect impact of the impact of such technology adoption (Becerril and Abdulai, 2010; David and Otsuka, 1994; de Janvry and Sadoulet, 2002; Minten and Barrett, 2008; Moyo et al., 2007).

The direct effects of new agricultural technology on poverty reduction are the productivity benefits enjoyed by the farmers adopting new technology. These benefits usually manifest themselves in the form of higher farm incomes. The indirect effects are productivity- induced benefits passed on to others by the adopters of the technology. These may comprise lower food prices, higher nonfarm employment levels or increases in consumption for all farmers (de Janvry and Sadoulet, 2002). However, productivity- enhancing agricultural technology involves a bundle of innovations rather than just a single technology. The impacts of higher-order (indirect) benefits from technology adoption depend: depend on the elasticity of demand, outward shifts in supply lowering food prices; and an increased productivity which may stimulate the demand for labor. The poor and marginal farmers tend to supply off-farm labor, which may translate to increased employment, wages, and earnings for them. They have little or no land and they gain disproportionately from employment generated by agricultural growth and from lower food prices. Higher productivity can, therefore, stimulate broader development of the rural economy through general equilibrium and multiplier effects, which also contribute to poverty reduction. Agricultural technology may induce changes in cropping patterns and allocation of farmers' own resources to different uses. It is important to notice that the technology adoptions may vary from farmer to farmer and the nature of the technology in use. For instance, technology adoption in agriculture can be either through high yield variety (HYV) seeds, advances in irrigation facilities, fertilizers, pesticides use or through the machinery employed during agricultural activities.

Mendola (2007) adopts a non-experimental evaluation strategy in order to assess the direct contribution of modern-seed technology adoption to rural poverty in Bangladesh. Using a cross-sectional household survey from rural Bangladesh, the study isolates the causal effect of adopting high yielding varieties (HYVs) of rice on poverty alleviation by using the "propensity-score matching" (PSM) method. According to the PSM estimation method, the adoption of HYVs of rice has a positive impact on farm household wellbeing. Allowing for interactions between agricultural technology and other determinants of income, this method leads us to quantify the positive impact of technology adoption on resource-poor farmers, in terms of rise of income and poverty reduction.

Minten and Berrett (2008) study in Madagascar also drew similar conclusion of adopting of intensifying improved technologies which is strongly associated with better agricultural yields. Karanja et al., (2003) showed that maize technology adoption in high agricultural potential regions of Kenya is likely to have substantially greater positive impacts on aggregate real incomes, but may have a less-than-positive influence on income distributional outcomes, compared to technology adoption in low agricultural potential regions. Becerril and Abdulai (2010) also uses PSM to analyze the impact of the adoption of improved maize varieties on household income and poverty reduction, using cross-sectional data of 325 farmers in Mexico. The findings reveal a robust positive and significant impact of improved maize variety adoption on farm household welfare measured by per capita expenditure and poverty reduction. The adoption of improved maize varieties helped in raising the household per capita expenditure by an average of 136-173 Mexican pesos, thereby reducing their probability of falling below the poverty line by roughly 19-31 percent.

Most of the studies on the impact of agricultural technology on farm incomes and poverty reduction focus macro approaches, with very few analyses at the micro-level. Some of the few household level studies include Evenson and Gollin (2003); Mendola (2007); and Moyo et al., (2007). Kassie et al., (2011) evaluates the ex-post impact of adopting improved groundnut varieties on crop income and poverty in rural Uganda. The study utilizes cross-sectional data of 927 households, collected in 2006, from seven districts in Uganda. Using PSM technique the study reports that adopting improved groundnut varieties (technology) significantly increases crop income and reduces poverty.

Thus, the literature appears to document overall positive impacts, with far less evidence at the individual household level that specifically show the effects of the adoption of agricultural technologies on farm productivity and household welfare. This study is a value addition in this regard in the context of Odisha. The objective of this paper is to assess the role of agriculture related technology adoption, on consumption expenditure and poverty status measured by headcount index, poverty gap index and poverty severity index. The empirical question that we would like to address is "*do agriculture related technology adoptions have the potential to reduce poverty?*" In understanding this question, we apply PSM method to deal with the selection bias problem. In addition to PSM, we also conduct the "*rbounds test*" and a "*balancing test*" using the "*mean absolute standardized bias*" between the agricultural technology adopters and non-adopters as suggested in Rosenbaum and Rubin (1985). The rest of the paper is organized as follows. Section-2 presents the analytical framework and the model, section-3 presents the data and descriptive statistics, section-4 presents the econometric results and section-5 concludes.

THE ANALYTICAL FRAMEWORK

One of the standard problems in impact evaluation involves the inference of the causal relations between the treatment and the outcome. There are two specific related problems with regards to evaluating the impact, of an intervention on targeted individuals; such as (1) the selection bias problem and (2) missing data problem in case of the counterfactual. There is extensive literature describing developments in addressing the problem stated above. Broadly, empirical literature categorizes evaluation methods in five categories such as; (1) pure randomized experiments (2) natural experiment (3) matching method (4) selection or instrumental variable model and (5) structural simulation model. This paper aims at indentifying the causal effect of adoption of agricultural related technologies on consumption expenditure and poverty using matching method on the non-experimental data. We follow Imbens and Angrist (1994), using counterfactual outcomes framework known as the Average Treatment Effect (ATE). Under this framework, it is assumed that each observational experimental unit with an observed outcome has ex-ante two potential outcomes: (1) an outcome when under adoption (that we denote y_1) and (2) an outcome when not under adoption (we denote y_0). Let y_i the *observed* overall expenditure for a household i. Thus y_1 and y_0 are two random variables representing, respectively, the potential expenditure level of household i when farmer participate in agriculture related technology adoptions $(d_i = 1)$ or does not participate $(d_i = 0)$. For any household i, the causal effect of participation in agriculture related technology adoption on household expenditure is defined as $(y_1 - y_0)$. However, the two potential outcomes can't be observed at the same time. We observe either y_1 or y_0. According to whether the household had participated or not, it is not possible to measure

$\left(y_1 - y_0\right)$ directly. The average causal effect of adoption within a specific population (ATE) can be determined as $E\left(y_1 - y_0\right)$, with E as the mathematical expectation.

Several methods have been proposed to estimate ATE, and they include the matching methods based on propensity scores, as well as parametric methods based on Instrumental variable methods. The choice of method is largely driven by the assumptions made and the availability of data. For any observational data (that is non-experimental) an important assumption is; the Conditional Independence Assumption (CIA), that states conditional on X (observables), the outcomes are independent of the treatment $\left(d\right)$ and can be written as:

$$y_{1,}y_0 \perp d \mid X \tag{1}$$

The behavioral implication of this assumption is that participation in the treatment does not depend on the outcomes after controlling for the variation in outcomes induced by differences in X. A much weaker assumption also used for *indentifiability* of the causal effect of the treatment is what Imbens and Angrist (1994) refers to as the *unconfoundedness* assumption, and which Rubin (1978) refers to as the *ignorability* assumption. The assumption is written as:

$$y_0 \perp d \mid X \tag{2}$$

If valid, the assumption implies that there is no omitted variable bias once X is included in the equation hence there will be no confounding. The assumption of *unconfoundedness* (equation-2) is very strong, and its plausibility heavily relies on the quality and the amount of information contained in X. A slightly weaker assumption also associated with the treatment effect evaluation is referred to as the "overlap or matching (common-support condition)" assumption. The assumption ensures that for each value of X , there are both treated and untreated cases. The assumption is expressed as follows:

$$0 < \Pr\left[d = 1 | X\right] < 1 \tag{3}$$

This implies that there is an overlap between the treated and untreated samples. Stated the other way round this also means that the control and treated populations have comparable observed characteristics. Under the assumption discussed above (CIA and overlap) the ATE on the Average Treatment Treated (ATT) can be identified as:

$$\begin{aligned} E\left(y_1 - y_0 | a = 1\right) &= E\left[E\left(y_1 - y_0 | d = 1, X\right)\right] \\ &= E\left[E\left(y_1 | d = 1, X\right) - E\left(y_0 | d = 0, X\right) | d = 1\right] \end{aligned} \tag{4}$$

Where, the outer expectation is over the distribution of X , in the subpopulation of participating households in agricultural related technologies. In observational data, it is not possible to calculate directly the difference in the outcome of interest between the treated and the control group or the ATE due to the absence of the counterfactual[1]. As a consequence, data may be drawn from comparison units whose characteristics match those of the treated group. The average outcome of the untreated matched group is assumed to identify the mean counterfactual outcome for the treated group in the absence of a treatment. The propensity score matching method matches treated and untreated cases on the propensity score rather than on the regressor.

[1] The counterfactual is a condition in which the same household is observed under treatment and without treatment. In reality a household can only be observed under either of the two conditions at a time and not under both.

The propensity score which is the conditional probability of receiving treatment given X , is denoted $P(x)$ written as:

$$p(x) = \Pr[d = 1 | X = x] \quad (5)$$

An assumption that plays an important role in treatment evaluation is the balancing condition which states that;

$$d \perp X \mid p(x) \quad (6)$$

This can be expressed alternatively by stating that, for individuals with the same propensity score the assignment to treatment is random and should look identical in terms of their x vector. The main purpose of the propensity score estimation is to balance the observed distribution of covariates across the groups of adopters and non-adopters (Lee, 2005). The balancing test is normally required after matching to ascertain whether the differences in the 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 and Abdulai, 2010). Although several versions of balancing tests exist in the literature, the most widely used is the mean absolute standardized bias (MASB) between adopters and non-adopters (Rosenbaum and Rubin, 1985). Additionally, Sianesi (2004) proposed a comparison of the pseudo R^2 and p-values of the likelihood ratio test of the joint significance of all the regressors obtained from the logit analysis before and after matching the samples.

After matching, there should be no systematic differences in the distribution of covariates between the two groups. As a result, the pseudo R^2 should be lower and the joint significance of covariates should be rejected. Given how sensitive the quasi-experimental methods are to assumptions, we conduct the sensitivity analyses based on the Rosenbaum's method of sensitivity analysis as we assume CIA crucially depends on the possibility to match treated and control units on the basis of a large informative of pre-treatment variables. The threshold level of welfare that distinguishes poor households from non-poor households is the poverty line. Using a poverty line, a number of aggregate measures of poverty can be computed. A more general measure of poverty proposed by Foster-Greer-Thorbecke (1984) belongs to a class of poverty measures is given as:

$$p_\alpha = \frac{1}{n}\sum_{i=1}^{q}\left[\frac{z-y_i}{z}\right]^\alpha 1(y_i - z) \quad (7)$$

Where, the poverty line is $(z), y$ is expenditure per capita of the ith household measured in the same unit as z , n is the total number of individuals in the population, q is total number of poor individuals whose income is less than the poverty line, $1(y_i - z)$ is indicator variable that takes value of one if the income is below the poverty line and 0 otherwise and a poverty aversion parameter that takes values of 0, 1, and 2, providing three commonly used indices of poverty; (1) poverty incidence as represented by the head count index, (2) intensity by the poverty gap index and (3) severity by the squared poverty gap index. The poverty line is a subsistence minimum expressed as in Rangarajan committee report (2014). Individuals who reside in households with consumption lower than the poverty line are then labeled "*poor*". Using the minimum food expenditure as an additional measure, we can identify the "*ultra poor*" households whose total consumption per capita on food and non-food items is lower than the minimum food expenditure.

DATA AND DESCRIPTIVE STATISTICS

The data were collected through a household survey conducted in Koraput district of Odisha state in India. The sample villages are the beneficiaries of various programmes of M. S. Swaminathan Research Foundation (MSSRF) initiatives on technologies related to agriculture. The households were randomly selected from Jeypore sub-district. This led to the selection of 296 households. Data were collected at village and farm-household levels. At the village level, data collected included crops grown and the village infrastructures. At the household level data collected included the farmer knowledge of varieties cultivated, household composition and characteristics, land and non-land farm assets, livestock ownership, household membership to different rural institutions, varieties and area planted, indicators of access to infrastructure, household market participation, household income sources and consumption expenses. In this study, adopters are classified as households who have adopted at least one of the agricultural technologies, out of maximum of 17 technologies as reported by the sample households during the primary survey. These technologies are in terms of "asset related" to "technology related" suitable for agricultural activities such as use of tractors, motor for irrigation etc. weighted against the land holding (net). Table-1 reports descriptive statistics, disaggregated at the adoption status.

Table 1 presents a comparison of some of the important indicators at household level distinguished between adaptors and non-adopters. We can observe from the table that income, income less from MGNREGA, expenses related to food and total expenses, share of income from primary and secondary sources, are statistically significant between two groups. However, expenses related to non-food, income from tertiary source, age and education of head of households are not statistically different between both the groups. Therefore, determinants of poverty can be different or similar based on the variables that are statistically different. Further, we also know that there are trade-offs in technology that generates direct and indirect effects. When land is unequally distributed, and if there are market failures and conditions of access to public goods that vary with farm size, then the optimum farming systems will differ across farms. Small holder may opt to adopt capital saving technologies, while larger farmers may prefer capital intensive technologies.

Table 1: Household Characteristics by Adoption Status

Variables	Non-adopters (n=107)	Adopters (n=189)	Full Sample (n=296)	Difference (t-test)
Total income	37297.680	48143.480	44222.870	2.495***
Income less from MGNREGA	36422.920	47202.210	43305.640	2.468***
Food expenses	18397.760	21339.760	20276.270	2.059***
Non-food expenses	5043.028	6289.159	5838.699	1.547
Total expenses	28098.790	34244.330	32022.800	2.354***
Share of income from primary Source	62.115	67.527	65.571	2.263***
Share of income from secondary source	23.773	19.806	21.240	2.362***
Share of income from tertiary Source	6.311	5.621	5.870	0.683
Age of head of household	45.607	43.042	43.970	1.535
Education of head of household	0.645	0.630	0.635	0.261

Source: Primary data collected by authors during 2014

Note: *** indicate statistically significant at 1%, MGNREGA- Mahatma Gandhi National Rural Employment Guarantee Act, income and expenses are presented in Indian rupees, 2014

Table 2 presents the distribution of sample households according to land holdings and adoption status. Consistent, with Bercerril and Abdulai (2010), the differences in the distribution of land between adopters and non-adopters suggest a positive correlation between the incidence of adoption and the ownership of land. The incidence of adoption is clearly higher among 1^{st} and 3^{rd} quartiles of land distribution compared to the other two distributions. Such differences in land ownership between adopter and non-adopters could also contribute to the disparities in welfare indicators between the two groups.

Table 2: Distribution of Sample Households by Landholding and Adoption Status

Quartile(s)	Non-adopters (n=107)		Adopters (n=189)	
	Frequency	Percentage	Frequency	Percentage
1st	16	14.95	44	23.28
2nd	21	19.63	31	16.40
3rd	23	21.50	67	35.45
4th	47	43.93	47	24.87

Source: Primary data collected by authors during 2014.

Table 3: Comparative Indicators Households

Variables	Non-adopters (n=107)	Adopters (n=189)	Full Sample (n=296)	Difference (t-test)
Technology score	0.034	0.205	0.143	11.232***
Agriculture related technology score	0.001	0.298	0.191	17.680***
Wet land as a ratio of total land	0.216	0.278	0.256	1.844*
Technology related expenses	4658.000	6615.413	5907.834	1.660*
Dry land as a ratio of total land	0.143	0.161	0.155	0.686
Total land in acres	2.300	2.687	2.547	0.937
Irrigated land as a ratio of total land	0.426	0.444	0.438	0.405

Source: Primary data collected by authors during 2014

Notes: *** and * indicate statistically significant at 1% and 10% level

Table 3 describes the comparative statistics between adopters and non-adopters household characteristics related to technology adoption and land holdings. Here, we have tried to compare the variables such as technology score, agriculture related technology score, components of land in terms of total land, irrigated, dry, wet land and technology related expenses. These components or indicators are compared between the two groups. The technology score and the agriculture technology score are differentiated based on the technology related to agriculture and non agriculture. The score for each of the groups are defined as a weighted score that is similar to the Human Development Index (HDI).

From table 3 we can observe that the sample, that is differentiated based on the adopters and non-adopters are statistically difference in terms of technology score, agriculture related technology score, ratio of wet land to total land and expenses related to technology at household level. Other than these variables, indicators such as ratio of dry land to total land, total land and ratio between irrigated and total land are not statistically different between two groups. Table-4 presents mean and median per capita consumption expenditure and the Gini coefficient by household grouped in different groups. There is a significant difference between the adopter categories in terms of welfare indictors.

Table 4, also presents the estimated mean and median per capita consumption expenditure, and the Gini coefficient by household based on household head's characteristics. A further close look at the distribution of total expenses data shows that it is also skewed. After transforming the consumption variable into the logarithm form, the distribution is normalized but the t-test still shows a significant difference in consumption expenditure between adopters and non-adopters. About 91.37 percent of the households live below the poverty line. The incidence of poverty is higher among the non-adopters (84 percent) than it is among adopters (78 percent) indicating an unconditional headcount ratio of poverty for the adopters of about 10 percentage points lower, compared to non-adopters. About 35 percent of the households are ultra poor implying that 35 percent of the households among the sample live in such dire poverty that they cannot even afford to meet the minimum standard of daily-recommended food requirement. The incidence of ultra poverty is also higher among non-adopters (46 percent) than among adopters (39 percent) suggesting that agriculture related technology adoption is positively correlated with wellbeing.

Table 4: Mean and Median Per Capita Consumption Expenditure, and the Gini Coefficient

	Mean	Median	Gini coefficient
Male headed households	18718.2	14435.2	30.5
Female headed households	12799.2	14435.2	25.0
Household adopted to agricultural related technology	19120.6	14435.2	32.1
Household not adopted to agricultural related technology	17324.8	14435.2	28.1
Full sample	18416.7	14435.2	30.5

Source: Primary data collected by authors during 2014.

Table 5: Sensitivity of Poverty Measures to the Choice of Indicator

	Poverty Headcount Rate	Poverty Gap	Squared Poverty Gap
Actual	91.4	53.2	34.3
Without technology adoption (absolute)	92.0	56.7	37.9
Without agricultural technology adoption (absolute)	93.5	59.7	41.1
With education	91.1	51.2	32.3
With technology score (relative)	89.7	49.1	30.3
With agricultural technology score (relative)	87.2	44.1	25.9

Source: Primary data collected by authors during 2014.

Table 5 presents the sensitivity of poverty measures to choice of indicator. This table gives the estimates of poverty headcount, poverty gap and squared poverty gap with and without some of the important indicators. For example, we can see that education reduces poverty up to -0.3 percent, higher technology score helps in reducing poverty up to 1.9

percent and agriculture technology score helps reducing poverty up to 4.5 percent. All the other indicators and results are given in Table 5.

ECONOMETRIC RESULTS AND DISCUSSION

Although, the unconditional summary statistics and tests in the tables above in general suggest that agriculture related technology adoption may have a positive role in improving household wellbeing, these results are only based on observed mean differences in outcomes of interest and may not be solely due to agriculture related technology adoption. They may instead be due to other factors, such as differences in household characteristics.

Table 6: Determinants of Adoption of Agricultural Related Technology

Independent variables	Coefficient	Std. Err.	z
Land holding of household	0.046	0.021	2.190***
Gender of head of household	-0.051	0.022	-2.318***
Age of head of household	-0.021	0.016	-1.313
Education of head of household	0.204	0.099	2.061***
Household size	-0.041	0.017	-2.412***
Income share from agriculture	0.021	0.011	1.909*
Ratio of wet land to total land	1.023	0.711	1.439
Ratio of dry land to total land	1.101	0.928	1.186
Technology score of household	7.981	3.551	2.248***
Participation in MGNREGA	-0.212	0.406	-0.522
Constant	-2.766	1.249	-2.215***
Number of observations	296		
LR $chi^2(10)$	186.840***		
Pseudo R^2	0.482		
Log likelihood	-100.245		

Source: Primary data collected by authors during 2014
Note: *, *** indicate statistically significant at 10% and 1% level, respectively

To measure the impact of adoption; it is necessary to take into account the fact that individuals who adopt agricultural technologies might have achieved a higher level of welfare, even if they had not adopted. As a consequence, we apply propensity score matching methods that control for these observable characteristics to isolate the intrinsic impact of technology adoption on household welfare. Table 6 provides information about some of the driving forces behind farmers' decisions to adopt agricultural technologies where, the dependent variable takes the value of one if the farmer adopts at least one agricultural related technology and 0 otherwise. The results show that the coefficients of most of the variables hypothesized to influence adoption, have expected signs and they include factors such as the land holding size, gender, education of head of the household, household size, income from agriculture, technology score of household etc. The size of the land owned by the household returned a positive and significant coefficient suggesting that farmers with larger holdings are more likely to adopt than small farmers. According to de Janvry et al., (2001) small farmers will typically prefer new farming systems that are more capital-saving and less risky while large farmers would prefer new farming systems that are more labor saving and they can afford to assume risks. In this case small farmers seem to avoid improved varieties due to the high costs associated with the purchasing of improved seed.

Among the explanatory variables, education of head of the household, income from agriculture, higher technology score of households are positively related to the decision to adopt the agriculture related technology. However, gender of head of the household, household size, are negatively related to the decision to adoption of agriculture related technology. Among the other variables, age of the head of the household, ratio of wet land to total land, ratio of dry land to total land and participation in MGNREGA, are not the major determinants of decision to participate in adopting the agriculture related technology at household level. Further, we have conducted the "*balance test*" for balancing of the distribution of relevant covariates between adopters and non-adopters before and after matching. Table-7 presents results of propensity score matching quality indicators before and after matching. The pseudo R^2 also increased significantly from 48 percent before matching to about 56 percent. This low pseudo R^2, high total bias reduction, and the significant p-values of the likelihood ratio test after matching suggest that, the specification of the propensity is successful in terms of balancing the distribution of covariates between the two groups.

Table 7: Adoption Effect on Per Capita Expenditure (Results from the PSM)

Matching algorithms	**NNMa**	**NNMb**	**KBMa**	**KBMb**
Pseudo R^2 before matching	0.482	0.482	0.482	0.482
LR chi^2 before matching	86.840***	86.840***	86.840***	86.840***
Mean standardized bias before matching	21.157	21.157	21.157	21.157
Pseudo R^2 after matching	0.561	0.543	0.541	0.541
LR chi^2 after matching	87.531***	89.541***	88.651***	88.567***
Mean standardized bias after matching	7.969	6.142	4.92	4.884
Total % bias reduction	62.329	71.678	76.797	76.989

Source: Primary data collected by authors during 2014

Note: *** indicate statistically 1% level; NNMa = single nearest neighbor matching with replacement, common support, and caliper (0.03); NNMb = five nearest neighbors matching with replacement, common support, and caliper (0.03); KBMa = kernel based matching with band width 0.03, common support and KBMb = kernel based matching with band width 0.06, common support.

Table 8: Impact of Agricultural Related Technology Adoption

Matching algorithm		Outcome (mean)		ATT
		Adopters	Non-adopters	
aNNM	Per capita expenditure	9.582	9.381	0.200 (2.10)***
	Head count ratio	0.586	0. 761	-0.174 (-2.67)***
	Severity of poverty	0.529	0.513	-0.015 (0.10)
bNNM	Per capita expenditure	9.582	9.414	0.167 (2.10)***
	Head count ratio	0.586	0. 761	-0.129 (-2.29)***
	Severity of poverty	0.529	0.509	0.020 (0.13)
aKBM	Per capita expenditure	9.582	9.415	0.166 (2.23)***
	Head count ratio	0.586	0.708	-0.121 (-2.20)***
	Severity of poverty	0.529	0.519	0.009 (0.05)
bKBM	Per capita expenditure	9.582	9.415	0.166 (2.29)***
	Head count ratio	0.586	0.709	-0.122 (-2.25)***
	Severity of poverty	0.529	0.523	0.006 (0.03)

Source: Primary data collected by authors during 2014

Note: *** indicates statistical significance at the 1%. T-statistics in parenthesis, aNNM = single nearest neighbor matching with replacement, common support, and caliper (0.03); bNNM = five nearest neighbors matching with replacement, common support, and caliper (0.03); aKBM = kernel based matching with band width 0.03, common support and bKBM = kernel based matching with band width 0.06, common support, Figures in parentheses at *t*-values

Table 8 reports the estimates of the average adoption effects estimated using nearest neighbor matching (NNM) and kernel based matching (KBM) methods. All the analyses were based on implementation of common support and caliper, so that the distributions of adopters and non-adopters were located in the same domain. As suggested by Rosenbaum and Rubin (1985), we used a caliper size of one-quarter of the standard deviation of the propensity scores. Three outcome variables are used in the analysis such as (1) per capita expenditure, (2) head count ratio, (3) severity of poverty index. The results indicate that, adoption of agriculture related technologies have positive and significant effect on per capita consumption expenditure and negative impact on poverty.

To gain further understanding of the impact of adoption on different groups of adopters, we also examined the differential impacts of adoption by dividing households into quartiles based on consumption, headcount ratio, depth of poverty, and severity of poverty. As observed in Table-9, the impact of adoption on consumption expenditure decreases with farm size. Interestingly, the gain in consumption expenditure and reduction in poverty is highest in the lowest farm-size quartile (1). These findings suggest that adoption of agricultural related technology can contribute to poverty reduction among the near landless households.

Table 9: Differential Impact of Adoption By Farm Size and Years of Experience

Stratified by farm size	1	2	3	4
Mean impact on household consumption	0.927 (3.0)***	0.273 (1.39)	0.145 (0.86)	0.058 (0.38)
Mean impact on headcount ratio	-0.667 (-4.0)***	-0.318 (-2.32)***	-0.129 (-100)	-0.075 (-0.57)
Mean impact on depth of poverty	-1.066 (-2.77)***	-0.296 (-1.81)*	-0.123 (-0.88)	-0.058 (0.27)
Mean impact on severity of poverty	1.209 (1.58)	0.151 (-0.94)	-0.21 (0.22)	0.061 (-0.13)

Source: Primary data collected by authors during 2014

Note: *, *** indicate statistically at 10% and 1% level, respectively

CONCLUSION AND POLICY IMPLICATIONS

The relationship between agricultural technology adoption and welfare is assumed to be straight forward. However, quantifying the causal effect of technology adoption can be quite complex. This paper provides an ex-post assessment of the impact of adoption of agricultural related technology on per capita consumption expenditure and poverty status measured by headcount index in rural India. Our results show that adoption has a positive impact on consumption expenditures and negative on poverty reduction. Though there is a large scope for boosting the role of agricultural technology in anti-poverty policies in rural areas. Implementing poverty alleviation measures, though, is not just the nature of technology but also the inclusion of a poverty dimension into the agricultural research priority-setting. Better targeting of agricultural research on resource-poor producers might be the main vehicle for maximizing direct poverty-alleviation effects. Improved agricultural technology diffusion seems the most effective means of improving agricultural productivity vis-à-vis reducing poverty. Improved rural infrastructure, improved irrigation systems, maintenance of livestock, physical assets, better access to education, secure land tenure, and reasonable access to extension services all play a significant role in encouraging productivity growth and poverty reduction. Technology adoption, however, is constrained by lack of development of market infrastructure, information asymmetry and agriculture extension services. Policies that address these constraints and strengthen local institutions to collectively improve access to technology, credit, and information will increase both the spread and intensity of adoption.

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