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ScienceDirect

Rice Science, 2020, 27(1): 56−66

Research Paper

Adoption and Impact of Modern Rice Varieties on Poverty in Eastern India

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Abstract: The factors affecting the adoption of modern varieties (MVs) of rice and impact on poverty in Odisha, India were discussed. A total of 363 households from Cuttack and Sambalpur districts of Odisha via multistage sampling technique participated in the survey. The Cragg's Double hurdle model was used to model the determinants of adoption and intensity of adoption of MVs of rice, and the propensity score matching was used to analyze the impact of adoption on poverty. The results showed that age, education, risk aversion, land size, yield, perception of MVs as high yielding, resistant to diseases and availability of MVs positively influenced the decision to adopt. However, variables such as household size, experience of a farmer, off-farm job participation, amount of credit received, cost of seeds, insecticides and fertilizers negatively influenced the adoption of MVs. Intensity of adoption of MVs was negatively influenced by experience of a farmer, cost of fertilizer and marketability of MVs, and positively affected by household size, risk aversion, land size, cost of insecticides, perception of MVs as high yielding and availability of MV seeds. Poverty incidence, gap and severity were high among non-adopters to adopters of MVs. After matching adopters and non-adopters of MV groups using four different algorithms of nearest neighbour matching, stratification matching, radius matching and kernel matching, the impact of MV adoption resulted in higher per capita monthly household expenditure by about US$ 52.82 to US$ 63.17.

Key words: rice; adoption; poverty; Cragg's Double hurdle model; modern variety

Rice is mostly cultivated in the rainfed and irrigated ecosystems as the principal crop of Eastern India (Samal et al, 2006; Singh et al, 2016; Dar et al, 2017). Odisha, one of the major producers of rice in Eastern India, records an average yield of 1 491 kg/hm^2 below the national average of 2 404 kg/hm^2. This is largely due to adverse abiotic stress on the rice plants during production, poor agronomic practices and the use of traditional varieties (Samal and Pandey, 2005; Mohapatra, 2014; Sarangi et al, 2016). As such, in some cases, farmers are hesitant to use agricultural inputs, leading to further reduction in the potential yield (Dar et al, 2017).

To increase rice productivity and ensure the wellbeing of rural people who are mostly dependent on rice, the Government of India through the All India Coordinated Rice Improvement Project (AICRIP) in conjunction with about 100 research institutions has released more than 620 modern rice varieties that can withstand various stress conditions (Janaiah et al, 2006). However, the adoption of modern varieties (MVs) of rice has still been low in Odisha (Paltasingh et al, 2017). It is reported that farmers adopted only 221 out of the 620 MVs of rice from 1998 to 2000 (Janaiah et al, 2006). It therefore seems to suggest that

Received: 5 August 2018; **Accepted:** 9 December 2018
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Peer review under responsibility of China National Rice Research Institute
http://dx.doi.org/

the time and funds spent on the development of MVs that can adapt to the stressful conditions are counterproductive if farmers do not adopt the MVs.

As a result, the socio-economic reasons for the adoption and non-adoption of MVs have been the major concern of various researchers and change agencies. Consequently, there have been surfeit of research work on variety adoption which have shown that adoption of MVs is influenced by series of factors (Matuschke et al, 2007; Rath et al, 2007; Wason et al, 2009; Barrett et al, 2010; Udry, 2010; Samal et al, 2011; Ghimire et al, 2012; Paltasingh et al, 2017). Most of these studies, however, used models ranging from zero-order correlation, multiple regression, Tobit models, bivariate logit/probit to multinomial probit and logit models, and proceeded on the assumption that the two decisions of adoption and intensity of adoption are jointly determined without any empirical separability tests. Therefore, informed recommendations from these studies could be misleading.

Furthermore, despite the glut of literature on adoption of MVs, there is a dearth of empirical research relative to the impact of the adoption on poverty reduction in Odisha or even in India. As such, most previous research fails to move beyond estimating the determinants of the adoption of MVs. As a result, they provide an impression that a knowledge of the factors influencing the adoption of MVs is enough to suggest policy recommendations without any further analysis of the impact of the adoption of these varieties on the welfare of the farm household.

This study, therefore, aimed to provide up-to-date empirical analysis on the determinants of adoption and intensity of adoption of MVs in Odisha. Additionally, the research also provided an empirical analysis of the impact of the adoption of these MVs on the poverty levels at individual farm household. Besides, this study also extended the frontiers in terms of methodological approach in addressing the research question which have not been used in Eastern India. The study, thus, provided useful information for policy formulation as well as making empirical contributions to adoption of modern technologies and impact assessment literature.

MATERIALS AND METHODS

Study area

Odisha, the tenth-largest state in India, is located on the eastern coast of the country. It is divided into 30 districts, 58 sub-divisions, 317 tahsils, 314 blocks, and 6 227 *Gram Panchayats,* spread over 51 349 villages administratively. It is a land of huge diversity with about 83.31% of the population living in rural areas. Rice, the principal crop of the region, is normally cultivated two ecosystems of rainfed and irrigated which are mainly found in the coastal, southern and northern regions of the state (Government of Odisha, 2014).

Sampling of respondents

Selection of districts, blocks, villages and rice farmers were done through a multistage sampling procedure. The research was conducted from December 2017 to April 2018. In the first stage, major producing districts in the two irrigated and rainfed ecosystems were chosen. In irrigated ecosystem, Cuttack district was selected whereas Sambalpur was selected for the rainfed ecosystem. Irrigated and rainfed blocks were selected from each of the districts in the second stage. From Cuttack district, Cuttack and Athagarh blocks were selected. Similarly, Panpali and Dhubenchapal blocks of Sambalpur were selected. Using a simple random technique, 6 villages were randomly selected with 25 farmers each. It was repeated in the two selected blocks at Cuttack district. Similarly, 2 villages with 25 farmers each were selected from each of the 2 blocks in Sambalpur. The different villages were selected to increase the diversity of responses which is essential for impact assessment. A total of 300 and 100 farmers were selected from Cuttack and Sambalpur districts, respectively. However, due to missing data, the data available used for this analysis consisted of 286 from Cuttack and 77 from Sambalpur districts. A structured questionnaire translated in *oriya* language was used to collect the data. Among these farmers selected, 114 were marginal farmers, 112 were smallholder farmers, 43 were semi-medium farmers, 93 were medium land size holder farmers and only 1 was a large holder farmer.

Additionally, three experts from biotechnology and plant breeding, rice taxonomy and agricultural extension at National Rice Research Institute, Cuttack, India, were interviewed for this research.

Analytical procedure

It is proposed that the individual's adoption decision of an MV is dichotomous, involving two mutually exclusive alternatives, the individual either adopts or does not (Martey et al, 2014). This is anchored on the utility maximization theory by Rahm and Huffman (1984). It assumed that the satisfaction obtained depends on several attributes which broadly included demographics, management and production characteristics of farmers and post-harvest characteristics. However, usually adoption moves beyond the initial decision to adopt or not. Farmers also decides on proportion of land (continuous decision) to allocate for the modern rice variety and intensity of adoption.

Specification of Cragg's Double hurdle model

The double hurdle model has been used severally on adoption of agricultural technologies researches (Martey et al, 2014; Ghimire and Huang, 2015; Amankwah et al, 2016; Asante et al, 2018). The model allows for modelling the two decisions of adoption and intensity of adoption as dependent variables (Garcia, 2013). Grounded on the random utility model in equations (1) and (2), we assumed that a farmer, facing with a set of alternatives, would select the alternative one that offers the highest utility (Greene, 2007; Greene and Henshe, 2010; Muthini et al, 2017; Banor et al, 2019).

A farmer, k faced with two choices, i and j with utilities U_i and U_j, can be expressed as:

$$U_i = X_{i1}W_{i1} + X_{i2}W_{i2} + \varepsilon_i \quad (1)$$

$$U_j = X_{j1}W_{j1} + X_{j2}W_{j2} + \varepsilon_j \quad (2)$$

Where W_{ij} are the individual farmer's own characteristics in the conceptual framework (Supplemental Fig. 1). The farmers' unmeasured characteristics otherwise known as the random terms is represented by ε_i and ε_j. If the farmer's choice of alternative i is denoted by $Y = 1$, then $U_i > U_j$, which follows:

$$Prob[Y = 1 \vdots W_{i1,} W_{i2,} W_{j1} W_{j2}] = Prob[U_i > U_j] \quad (3)$$

$$Prob[x'\beta + \varepsilon > 0 \vdots X] \quad (4)$$

Where $x'\beta$ represents measured elements of the difference of the two utility functions with ε as the difference between the two random elements (Muthini et al, 2017).

There are two schools of thought in adoption studies. Firstly, the situation where the two decisions (discrete and continuous) are affected by the same set of factors; with this, the Tobit model is preferred (Amankwah et al, 2016). Secondly, the circumstances where the two decisions are not jointly determined by the same factors; the Cragg's double hurdle or Heckman selection models are preferred (Katchova and Miranda, 2004). As a result of these two schools of thought, the study also applied the one step Tobit model for comparison with the two step models procedure as discussed subsequently.

Two-step procedure

The probit and truncated regression models were used in the Cragg's double hurdle model. The probit regression estimated the probability of adopting MVs (Cragg, 1971; Muthini et al, 2017). Thus, where y is either 0 or 1, it can be expressed as:

$$Prob(y > 0) = \Phi x'\beta \quad (5)$$

Whereby Φ is the symbol of normal distribution.

Afterwards, the farmer intensity of adoption decision was analysed by the use of the truncated regression. It can be presented as:

$$E(y \vdots y > 0) = x' + \beta + \delta\lambda(x'\beta/\delta) \quad (6)$$

The term $x'\beta/\delta$ is an adjustment factor, indicating a farmer who did not adopt MV be dropped in the analysis (Muthini et al, 2017).

Decision on the choice of one step model or two step models in this research was grounded on the log-likelihood values from the probit, Tobit and truncated regression models as presented in equation (7). The likelihood ratio test statistic λ was estimated as follows:

$$\lambda = -2(LL_{\text{Probit}} + LL_{\text{Truncated}} + LL_{\text{Tobit}}) \quad (7)$$

The two stage models of Cragg's double hurdle and Heckman selection models were selected because the estimated value of λ was greater than *Chi* square ($\chi_{0.1}$) critical value (Muthini et al, 2017; Asante et al, 2018; Bannor et al, 2019).

Construction of poverty line

Monthly per capita expenditure was chosen as an indicator for the measurement of a household poverty status in the study. The agreed poverty line which is \$11.39 (₹695.00) monthly per capita expenditure for rural areas was used in this analysis (Government of Odisha, 2018). Additionally, following the procedure of Bannor and Oppong-Kyeremeh (2018), who defined relative poverty line as the two-thirds of the mean per capita expenditure of surveyed households in the study area, the relative poverty line for this study was constructed to be \$4.59 (₹280.00) per month.

Measurement of poverty

After the classification of households as poor and non-poor based on the two poverty lines, the three poverty dimension instruments of Foster-Greer-Thorbecke (FGT) model namely headcount or poverty incidence, poverty gap, and severity indices were used to measure the extent of poverty and poverty level among rural sampled farmers. FGT model can be generally expressed as:

$$P_\alpha = \frac{1}{N}\sum_{i=1}^{q}\left(\frac{Z - Y_i}{Z}\right)^\alpha \quad (8)$$

where P_α is poverty measure or index; Z is poverty line; N is number of households in the population; q is number of households below the poverty line; Y_i is household per capita monthly expenditure; α is poverty parameter (incidence, gap and severity) which takes the values 0, 1 and 2.

Impact of modern variety adoption on poverty

The impact of MV adoption on poverty was analysed using propensity score matching (PSM). After fulfilling the conditional independence and the common support condition assumptions of PSM, the average treatment effect on the treated (ATT) estimation was used for the impact assessment.

According to Luan et al (2015), ATT can be mathematically expressed as:

$$ATT = E(\Delta|p(x), D = 1)$$
$$= E(y_1|p(x), D = 1) - E(y_0|p(x), D = 0) \quad (9)$$

where $E(y_1|p(x), D = 1)$ represents outcome for adopters and $E(y_0|p(x), D = 0)$ represents outcome for non-adopters.

ATT is estimated as follows:

$$ATT = \frac{1}{n_1}\sum_{i\in\{D=1\}}\left[y_{1,i} - \sum_j w(i, j)y_{0,j}\right] \quad (10)$$

Where each treated observation i is matched j control observations and their outcomes y_0 are weighed by w. Additionally, n_1 is the number of recipients; $y_{1,i}$ is the outcome for the recipient i; $y_{0,j}$ is the outcome for the matched non-recipient j; and $w(i, j)$ are weights.

Checking of robustness of PSM model

According to Jimenez-Soto and Brown (2012), there is a potential limitation of extending the PSM method since certain unobservables of household members could be correlated with the adoption decision. As a result, several proposals have been made to reduce the biases that may arise from using PSM or to ensure the robustness of the estimates. Jimenez-Soto and Brown (2012) proposed the use of large number of covariates to reduce biases. Another solution is to apply the direct nearest-neighbour matching instead of estimating the propensity score equation first. If both methods give similar results, the findings are assumed to be more reliable (Khandker et al, 2010). Kassie et al (2010) proposed the use of Rosenbaum bounds procedure to reduce biases while Davis and Nkonya (2008) addressed the problem by the combining PSM with the double-difference estimation. In this study, the robustness of the PSM estimates was checked according to Abadie et al (2004). These simple simulation exercises supported the robustness of the matching estimate used for this analysis.

Description of variables used in analysis

Farmers who used MVs and those who cultivated traditional varieties were defined as adopters and non-adopters, respectively. The characteristics of the sampled farmers and various variables are shown in Table 1. The decision and the intensity of adoption of MVs were expressed as discrete and continuous dependant variables. The explanatory variables are broadly under four main different characteristics namely demographic, management, production and post-harvest as shown in the conceptual framework (Supplemental Fig. 1). Variables such as caste, age, risk aversion of farmer, off-farm job participation, seed cost, insecticide and NPK cost were all expected to negatively influence adoption and intensity of adoption of MVs in Odisha. In contrast, education, household size, experience, farm records, access to credit and amount of credit received, farmer-based organisation membership, land size, number of plots, yield of rice variety planted, perception of MVs as high yielding, disease-resistant, easy accessibility of seeds and marketing were hypothesised to positively influence discrete and continuous decision of adoption of MVs in Odisha. However, the prone of a farmer's farm to flooding was hypothesised to either influence positively or negatively the discrete and continuous decisions of adoption of MVs in Odisha.

RESULTS

From Table 2, the poverty status of adopters indicated that 97.1% were not poor whilst 2.9% were poor. However, the percentage of poor households among non-adopters was 35.5%. Also, the intensity of adoption revealed the majority of the adopters represented by 73.7% had allocated more than 90% of their total land size to the cultivation of MVs and about 12% was between 31%–60% with only 5.2% allocating less than 30% of land for the cultivation of MVs. Further, the major sources of traditional varieties in the study area were farmers (Supplemental Table 3). In contrast, the major source of MVs was from the accredited dealer which was represented by

Table 1. Description of variables to be used in factors and intensity of adoption analysis.

Variable	Description	Measurement	Expected sign	Mean	*SD*
Dependent variable					
Adoption of new rice variety	Adoption of new rice variety	1 = Adopters, 0 = Non-adopters	Nil	0.950	0.217
Adoption intensity	Percentage of total land allocated to new variety for production	Proportion of land allocation	Nil	83.942	30.110
Independent variable					
Demographic characteristics					
Age	Number of years from birth	Number	-	47.124	10.183
Education	Highest formal educational level attained	School years	+	5.438	5.578
Household size	Number of adult household members	Number	+	2.234	2.238
Caste	Minority / lower caste	1 = Yes, 0 = Otherwise	+	0.061	0.240
Experience in rice farming	Number of years in rice farming	Number	+	26.335	17.759
Management characteristics					
Farm record	Keep farm records	1 = Keep records, 0 = Otherwise	+	0.405	0.492
Risk aversion	Growing of other crops in addition to rice as proxy for risk aversion	1 = Risk averse, 0 = Otherwise	-	0.877	0.329
Off-farm job	Participation in off-farm job	1 = Yes, 0 = Otherwise	-	0.438	0.497
Access to credit	Having received credit for 2016–2017 production year	1 = Yes, 0 = Otherwise	+	0.235	0.424
Amount of credit received	Total amount of credit received for 2016–2017 production year	Amount in rupees	+	955.934	7175.050
Membership of FBO	Membership of FBO	1 = Yes, 0 = Otherwise	+	0.237	0.426
Production characteristics					
Land size	Average land size planted for 2016–2017	Hectares	+	2.616	2.641
Number of rice plots	Total number of plots used for rice production	Number	+	5.478	4.213
Flood	Land is prone to floods	1 = Yes, 0 = Otherwise	+/-	0.253	0.436
Seed cost	Average total cost of seed for production	Amount in rupees	-	1172.860	5479.500
Insecticide cost	Average total cost of insecticide for production	Amount in rupees	-	1819.350	6776.610
NPK cost	Total cost of NPK for production	Amount in rupees	-	10883.250	37037.880
Yield	Average number of bags of rice harvested for 2016–2017	Number	+	17.337	32.522
High yielding	Perception of MVs with high yielding	1 = Yes, 0 = Otherwise	+	0.275	0.447
Disease resistance	Perception of MVs with disease resistance	1 = Yes, 0 = Otherwise	+	0.255	0.436
Seed availability	Ease accessibility of MV seeds	1 = Yes, 0 = Otherwise	+	0.275	0.447
Post-harvest characteristics					
MV easily marketable	Perception of MVs being highly marketable	1 = Yes, 0 = Otherwise	+	0.160	0.367

FBO, Farmer based organization; MV, Modern variety.

about 69.7% of the 310 MV adopters interviewed. From Table 3, unusually, increase in age relatively favoured the decision to adopt MVs in the study area by 0.43%. It was however not a significant indicator of the intensity of adoption of MVs in the study area. Adoption of improved varieties was positively associated with the level of education of a farmer. Adoption of MVs on the other hand was negatively correlated with household size by 4.5% but positivity linked to intensity of adoption by 2.4%.

Further, the discrete and continuous decision of MV adoption were positively influenced by risk aversion. Additionally, off-farm job participation decreased the likelihood of adopting rice MVs by 11.3%. As expected, adoption and intensity of adoption of rice MVs were increased by about 3.1% and 5.1%, respectively when land size increased by one hectare. Lastly, MV yield, resistance to diseases and seed availability increased the probability of adoption by 4.6%, 3.5% and 4.0%, respectively. Aside these factors, other determinants such as caste, farm records, farmer based organisation (FBO) membership, land prone to floods and number of rice plots were not found to significantly affect either discrete decision of MV adoption or continuous decision of intensity of MV adoption.

A presentation of the variances in the incidence, gap and severity of poverty for adopters and non-adopters using the two different poverty lines as explained in the method are given in Table 4 and Supplemental Table 1. Poverty incidence among adopters was 15.6% compared to 52.9% of non-adopters. Thus, for every 100 adopters, about 16 of them are poor whereas 53 out of 100 non-adopters of MVs are poor. Given that relative poverty line was used, the incidence of poverty was also very high

Table 2. Poverty and intensity of adoption of sampled respondents.

Variable	Adopter		Non-adopter		Overall	
	Frequency (*n* = 346)	Percentage (%)	Frequency (*n* = 17)	Percentage (%)	Frequency (*n* = 363)	Percentage (%)
Poverty status						
Poor	10	2.9	6	35.3	16	4.4
Non-poor	336	97.1	11	64.7	347	95.6
Intensity of adoption						
1–30	18	5.2				
31–60	42	12.1				
61–90	31	9.0				
>90	255	73.7				

Table 3. Factors influencing adoption and intensity of adoption modern varieties.

Variable	Double hurdle estimate		Tobit regression	Heckman estimate	
	Hurdle 1 (Probit regression)	Hurdle 2 (Truncated regression)		Probit regression	Ordinary least squares
Demographic characteristics					
Age	0.0043** (0.0019)	0.0016 (0.0016)	0.0016 (0.0016)	0.1538** (0.0727)	0.0022 (0.0026)
Education	0.0179* (0.0101)	0.0119 (0.0226)	0.0119 (0.0227)	0.6328 (0.6041)	0.0163 (0.0363)
Caste	-0.0536 (0.0399)			-1.3784 (2.4230)	
Household size	-0.0452*** (0.0172)	0.0243* (0.0136)	-0.0244* (0.0137)	-1.5981* (0.9176)	-0.0209 (0.0142)
Experience	-0.0032** (0.0014)	-0.0015* (0.0009)	-0.0015* (0.0009)	-0.1128* (0.0600)	-0.0027* (0.0016)
Management characteristics					
Farm records	0.0125 (0.0246)			0.4734 (1.1471)	
Risk aversion	0.1256*** (0.0415)	0.1319* (0.0831)	0.1312* (0.0832)	2.9912** (1.2257)	0.1600* (0.0779)
Off-farm	-0.1128*** (0.0279)	0.0074 (0.0607)	0.0072 (0.0614)	-3.2509** (1.2601)	0.0008 (0.0569)
Credit		0.0493 (0.0520)	0.0500 (0.0522)		-0.0199 (0.0670)
Amount of credit	-0.0000412* (0.0000)			-0.0000412 (0.0000)	
FBO membership		0.0290 (0.0573)	-0.0170 (0.0576)		0.0035 (0.0676)
Production characteristics					
Land size	0.0319*** (0.0010)	0.0534*** (0.0178)	0.0537*** (0.0181)	1.1300* (0.6953)	0.0481* (0.0129)
Number of rice plots		0.0044 (0.0073)	0.0045 (0.0073)		-0.0002 (0.0071)
Flooding land	0.0059 (0.0169)			0.2162 (1.2032)	
Seed cost	-0.00002* (0.0000)			-0.0006 (0.0004)	
Insecticide cost	-8.46e-06* (5.16e-06)	0.00004*(0.00002)	-4.28e-07 (4.02e-07)	-0.0003 (0.0004)	0.0000 (0.0000)
NPK cost	-1.47e-07 (5.84e-06)	-0.00006* (0.00004)	2.05e-07 (4.58e-07)	0.0000 (0.0004)	0.0000 (0.0000)
Yield	0.0040*** (0.0015)			0.1427* (0.8585)	
MVs high yield	0.0457*** (0.0167)	0.1317** (0.0585)	-0.1317 (0.0585)	1.9609 (1.3097)	0.1212** (0.0638)
MVs resistant to diseases	0.0351*** (0.0127)			1.9082 (1.6247)	
MVs seed availability	0.0400** (0.0170)	0.0972* (0.0609)	0.0988** (0.0619)	1.5497* (0.9122)	0.1385** (0.0622)
Post-harvest characteristics					
MV easily marketable		-0.0102 (0.0560)	-0.0090 (0.0567)		0.0334 (0.0780)
Constant	3.8425** (1.8949)	4.4946*** (0.1123)	4.4951*** (0.1125)	3.8412* (2.2493)	4.4692 (0.1463)
No. of observations	264	331	331		257
Wald chi2(18), (15) for truncated and heckman, (15)	45.22	64.16			44.22
Prob > χ^2	0.0004	0.0000			0.0001
Pseudo R^2	0.6571	–	0.1917		--
Inverse mills ratio *P* value					0.313
Log pseudo likelihood	-13.46	-1672.67	-117.74		--
Lambda (ʎ)	3136.78				
$\chi_{0.1}$	25.99				

Robust standard errors of Double herdle model and Tobit, and standard errors for Heckman Selection Model are in the parentheses. Lambda (ʎ) > $\chi_{0.1}$ = Reject the null hypothesis. *, ** and *** indicate significant differences at the 0.10, 0.05 and 0.01 levels, respectively.

among non-adopters represented by 35.3% to 2.5% among adopters.

From Table 5, per capita monthly household expenditure was used as a proxy variable for poverty. Unambiguously, the nearest neighbour matching estimates suggest that the impact of the adoption of MVs on household per capita monthly expenditure was about ₹3222.00 (US$ 52.82). Radius matching recorded the highest impact of the adoption of MVs on household per monthly expenditure with an amount of ₹3853.17, which is approximately US$ 63.17. Largely, after matching treated (adoption of MVs) and

Table 4. Estimates of poverty situation indicators using objective poverty line. %

Poverty variable	Adopter	Non-adopter	Overall	Odisha government
Headcount index	0.156 (15.6)	0.529 (52.9)	0.174 (17.4)	0.357 (35.7)
Poverty gap index	0.062 (6.2)	0.322 (32.2)	0.074 (7.4)	0.070 (7.0)
Poverty severity index	0.033 (3.3)	0.197 (19.7)	0.041 (4.1)	0.020 (2.2)

Partial data are from Government of Odisha (2018). Rural poverty index by Odisha Government are used. Objective Poverty line: $11.39 (₹695.00).

control (non-adoption of MVs), the effects of adoption of MVs has resulted in higher per capita monthly household expenditure by about ₹3222.00 (US$ 52.82) to ₹3853.17 (US$ 63.17) using the four different algorithms. Following the procedure by Abadie et al (2004), we checked the robustness of our PSM estimates. The estimation procedures used were sample average treatment effect (SATE), sample average treatment effect on the treated (SATT), the bias-corrected matching estimation and variance estimation allowing for heteroskedasticity (Supplemental Table 2). From the SATE analysis, the result suggested that, the average effect of adopting MVs causes an increase in per capita monthly household expenditure by ₹3585.837 (US$ 58.78). Likewise, the SATT estimates show the effect of the adoption of MVs on the farmers was ₹3525.87 (US$ 57.80).

DISCUSSION

Coastal Odisha is one of the most flood prone areas of India where the paddy crop in the wet season is often devastated by marauding floods, compelling farmers to either discontinue rice production or return to traditional varieties with very low yields (Dar et al, 2017). The study area continuous to experience several natural calamities such as flood and drought over the years. Historically, development of MVs has been of great importance to these old farmers. For example, Swarna-Sub 1 is a flood-tolerant MV for farms that are flooded during the monsoons. Additionally, Satyabhama (CR Dhan 100) was developed for farms susceptible to drought. Also, a highly adopted rice variety Pooja in Odisha is tolerant to major pests and diseases in the area.

The analysis showed a positive influence of age on adoption of MVs in contrast to the plethora of studies by Chandio and Jiang (2018). Abdulai (2016) and Marenya and Barrett (2007) who found a rather negative effect of age on adoption of MVs. One plausible reason is the experience these aged farmers have had over the years. Thus, the older you are in Odisha, the better you appreciate the importance of MVs in the area.

The positive effect of education on adoption of MVs (especially Pooja) is also reported by Bezu et al (2014), Ghimire and Huang (2015) and Khonje et al (2015) for maize varieties and Ghimire et al (2012) and Chandio and Jiang (2018) for rice varieties. The results are however in contrast to Tanellari et al (2014) who reported education has negative effect on the adoption of groundnut varieties in Uganda. Also, from our study, education did not influence the intensity of adoption. This differs with Paltasingh (2018) who found out that education increases the adoption intensity of rice in Odisha. From the research, it presupposes that a higher education is associated with an increase in the probability of adopting MVs but not intensity of adoption.

The negative effect of household size on adoption of MVs differs with a surfeit of studies on adoption such as Tanellari et al (2014), Bezu et al (2014) and Jena and Grote (2012) on Basmati rice adoption. This can be ascribed to the reduced and continuous lack of interest by the youthful members of families in rural India. However, it is consistent with results by Verkaart et al (2017) and Paltasingh et al (2017).

More so, the negative effect of experience in the adoption and intensity of adoption of MVs differs with studies such as Wongnaa et al (2018) on adoption

Table 5. Matching estimates of sample average treatment effect on the treated (SATT).

Estimation method	Per capita expenditure (₹)	SE (₹)	*t* test	No. of treatments	Number of controls
SATT nearest neighbour matching	3 222.00	566.17	5.69	346	13
SATT stratification matching	3 250.27	495.02	6.57	346	17
SATT radius matching	3 853.17	704.94	5.47	74	13
SATT kernel matching	3 268.36	466.30	7.00	346	17
Regression with dummy	3 601.96	682.34	5.28	–	–

Computation based on field data in 2018. 1$ = ₹61.

of MVs in Ghana, Chandio and Jiang (2018) on adoption of MVs in Pakistan, and Paltasingh et al (2017) on adoption of MVs of rice in Odisha. Assigning reasons, Wozniak (1987) argued that in a rapidly changing technological environment, experience may depreciate faster, hence only the current experience might be useful in making adoption decisions. Ainembabazi and Mugisha (2014) indicated that a negative relationship can be attributed to the asymmetric relationship between adoption and experience in farming especially when the current technology is like the traditional ones that farmers are in the known.

The results contrast with findings by Boucher et al (2008), Mariano et al (2012), Carter et al (2016) and Goswami et al (2016) on risk aversion. They argued that, risk directly discourages technology adoption by making farmers unwilling to productively invest their own savings, which will cushion them against income shortfalls. The conceivable reason for the positive relationship between risk aversion and adoption of MVs in Odisha can be ascribed to the crop production cycle in Odisha. Accordingly, farmers have overwhelming preference to cultivate rice in the wet season with legumes, vegetables and green gram (*Vigna radiata*) in the dry season (Dar et al, 2017). The results do not in any way suggest that diversification will reduce the interest of farmers adopting MVs. Singh et al (2016) and Dar et al (2017) have shown that farmers continually adopt MVs because of their resilience and tenacity to the floods and drought in Odisha especially those in lowland towns of Cuttack district.

Furthermore, cultivation of most MVs demand the use of certified seeds and fertilizer every year, however, considering the poverty levels in Orissa State of India, increases in the cost of seeds and fertilizer by either government artificial speculation or hoarding by sellers can greatly harm the adoption of MVs. This is always evidently clear with most pro-poor projects in most parts of the world especially developing countries like India where farmers discontinue the production of MVs at the end of free supply of seeds and fertilizers or reduction of subsidies on the same.

The positive effects of the availability of MVs on adoption of MVs are similar to studies by Afolami et al (2015), Ghimire and Huang (2015) and Paltasingh et al (2017). The results validate the importance of having accredited dealers of MV shops close to farmers' farms and households.

The results obviously suggest that poverty incidence among non-adopters is even higher than the aggregate poverty incidence in Odisha. Poverty gap index shows how much of Indian rupees should be transferred to the poor to escape poverty (Mada and Bannor, 2015; Bannor and Oppong-Kyeremeh, 2018). Using relative poverty line, poverty gap was the highest among non-adopters compared to adopters. Similarly, the highest poverty gap and severity were recorded among non-adopters to adopters when Government of India's objective poverty line was used. The results on poverty gap indicate that the cost of eliminating poverty among non-adopters is much higher than adopters and at the state level. Accordingly, regardless of the poverty line chosen, poverty, measured by poverty incidence, gap and severity is explicitly lower for adopters than non-adopters. This result accentuates MV contribution to poverty reduction.

Evidently, the results suggest the adoption of MVs impact positively on the per capita monthly expenditure of rice producing households in Odisha, which are generally in line with impact studies of adoption of MVs in Asia, South America and Africa (Becerril and Abdulai, 2010; Jena and Grote, 2012; Khonje et al, 2015). To check the robustness of the PSM model used in the analysis, we used SATT which allows for heteroskedasticity. However, the results remained significant at the 1% level, even when the standard error is estimated under this weaker condition. This reemphasise that the adoption of MVs has impact on the per capita monthly household expenditure (poverty) of adopters.

CONCLUSIONS

From the study, demographic characteristics such as age and education positively affected the decision to adopt MVs whereas only household size positively affected the intensity of adoption. In contrast, household size and experience negatively affected the decision of a farmer. Management characteristics such as risk aversion of a farmer positively affected the discrete and continuous decision of adoption. Off-farm job participation and amount of credit received by the farmer negatively affected decision to adopt MVs. Production characteristics such as land size positively influenced adoption but negatively affected intensity of adoption. Likewise, the cost of seeds, insecticides and fertilizer negatively affected adoption and intensity of adoption decisions. Moreover, yield of rice, perception of MVs as high yielding, resistant to diseases and the availability of MV seeds positively affected the discrete decision to adopt and intensity of adoption of MVs.

Furthermore, poverty incidence among adopters was 15.6% compared to 52.9% of non-adopters. Similarly, the highest poverty gap and severity were recorded among non-adopters to adopters. The results therefore suggested that adopters of MVs were better off than non-adopters. A propensity score-matching model was used to analyze the impact of adoption on poverty because it can account for selectivity bias due to the nonexperimental nature of the data used in the study. Largely, after matching adopters and non-adopters using four different algorithms, adopters have a higher per capita monthly household expenditure between ₹3222.00 (US$ 52.82) and ₹3853.17 (US$ 63.17). Likewise, the sensitivity analysis results showed that the adoption of MVs had a significant impact on the per capita household expenditure of adopters.

In the context of policy recommendations, it is recommended that the closeness of MVs sale outlets to farmers' farms should be encouraged as it greatly influences farmers' adoption decision. Additionally, the cost of MV seeds should be carefully managed as it can reduce the interest of adopting MVs. Moreover, government of Odisha and India should critically consider MV adoption as one of the strategies to reduce poverty levels in Odisha since it positively impacts poverty reduction among farmers. Finally, in terms of method, it could be misleading to assume that adoption and intensity of adoption decisions are jointly determined as widely done in most studies in India without any separability and selectivity tests. It is therefore recommended that future studies in India should consider these tests for the determination of the appropriate estimation.

ACKNOWLEDGEMENTS

This work was supported by Federation of Indian Chambers of Commerce & Industry (2017–2018) through the Government of India under CV Raman Post-Doctoral Fellowship for African Researchers. Additionally, we are grateful to Mr. Chinmaya ROUT for his tremendous assistance during the data collection and entry. The logistical support of National Rice Research Institute during and after the data collection is duly acknowledged. Lastly, we express our heartfelt appreciation to the rice farmers of Cuttack and Sambalpur who spent time to answer the questionnaires.

SUPPLEMENTAL DATA

The following materials are available in the online version of this article at http://www.sciencedirect.com/science/journal/16726308; http://www.ricescience.org.

Supplemental Table 1. Poverty situation indicators using relative poverty line.

Supplemental Table 2. Estimation of sample average treatment effect (SATE) and sample average treatment effect on the treated (SATT).

Supplemental Table 3. Sources of traditional and modern varieties.

Supplemental Fig. 1. Conceptual framework.

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(Managing Editor: LI Guan)