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RESEARCH



# Farmers' risk attitude, agricultural technology adoption and impacts in Eastern India

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## Abstract

**Background** Agricultural production is inherently risky, as farmers are exposed to multiple stresses. The adoption of improved agricultural practices could become a key coping strategy to sustain production in such a risky environment. As several technologies are being developed and disseminated along this line, it is important to examine the factors influencing farmers' adoption of these strategies and their impact on productivity. Using survey data of rice growing farmers from eastern states of India, we tested how farmers' risk attitudes influence their decisions to adopt improved agricultural practices and whether the adoption has any influence on rice productivity.

**Results** Risk-seeking farmers are more likely to adopt mechanization, whereas risk-averse farmers are more likely to adopt stress-tolerant rice varieties (STRVs), which represent a low-/no-capital-cost improved technology. Adoption of these improved technologies has resulted in productivity gains. Yet, their overall adoption is (s)low in India and other developing countries, presenting a broader challenge of suboptimal productivity and requiring deeper policy engagement.

**Conclusions** Adoption of STRVs and mechanization has been found to have positive impact on rice productivity. These two agricultural technologies, as our results reveal, are adopted by two distinct categories of farmers depending on their risk attitude. However, both technologies could play a complementary role increasing and stabilizing rice production of farmers, and that is where scope for policy lies to bridge this gap. Targeted policy measures such as subsidizing the purchase of machineries for establishment of custom hiring centers, implementing effective extension mechanisms, and integrating STRVs in the seed systems to enhance physical and economic access to these technologies, could significantly increase their adoption and consequently improve productivity and income of farmers.

**Keywords** Risk attitude, Smallholder, Technology adoption, Productivity gain, India

**JEL Classification** Q12, Q16

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## Introduction

Vulnerability has emerged as a major concern for the sustainable intensification and food security of smallholder farmers in developing countries due to the inherent risky nature of agricultural production. The increased intensity and frequency of weather shocks are regularly affecting crop productivity [1, 2]. Besides these weather shocks, labor scarcity due to rural outmigration, land fragmentation, and water scarcity are some of the main factors affecting sustainable intensification and the welfare of smallholder farmers. Key strategies farmers often adopt to cope with these stresses include adjustments in farm practices (including crop/varietal diversity and input and other management practices), selling of liquid assets, migration, other income diversification, saving and borrowing, decreasing consumption, and receiving assistance from the government [3–7]. The adoption of improved agricultural technologies is considered paramount for coping with multiple stressors and sustaining agriculture production. However, many of the improved technologies face (s)low adoption, leading to a broader challenge of suboptimal productivity and requiring deeper policy engagement. A majority of the studies emphasize that the adoption of these strategies largely depends on the asset holdings (physical, financial, natural, human, and social) [8–14] and access to information [15]. Furthermore, farmers' behavioral responses to risks could also play an important role in their livelihood and welfare. To the best of our knowledge, there is not enough evidence on how farmers' risk attitudes affect their decision making on agriculture technology adoption and its implications on agricultural productivity. We, therefore, study the risk attitudes of farmers that affect their decisions related to investment and technology adoption [16, 17], as well as the impact of adoption on rice productivity.

There is a general consensus in the literature on 'risk induced poverty traps' that the majority of smallholder farmers are risk averse [18–20], resulting in their continued engagement in subsistence farming through the adopting low-cost low-return agricultural practices [20–23]. However, Jianjun [24] found the effect of risk attitudes on adoption varied across different adaptation strategies and improved practices. The adoption of both risk-reducing technologies (e.g., stress-tolerant varieties (STVs)) and investment under a risky scenario (e.g., mechanization) is important for sustainable intensification. STVs are low-cost, highly recommended risk-reducing technologies that are effective under low to moderate risk levels [15, 25–27]. Although mechanization often entails a capital cost, it is found to be an effective labor-saving technology that could also improve farm efficiency under existing conditions [11, 12, 28] and address labor scarcity. We argue that the assumption of risk-averse farmers not adopting modern technologies within the framework of the risk-induced poverty trap may apply only to capital-intensive technologies such as hybrid technologies [29], mechanization, etc. In this study, we select both capital and non-capital intensive technologies and test this hypothesis in the rice system of India.

Using primary data from four eastern states of India, we profiled farmers' risk attitudes (using a zero-inflated ordered probit model). Then, using an Endogenous Switching Regression (ESR) approach, we examined the effect of risk attitude and other factors on the adoption of improved agricultural practices and the impact of their adoption on rice productivity. Several widely recommended practices, such as mechanization, stress-tolerant varieties, and seed replenishment, were selected to estimate farmers' adoption. The article is structured as follows: "Study area and data" section provides details of the study area, sampling framework, and data collected; "Research design" section presents the experimental design of risk elicitation and econometric specifications; ""Results and discussion"" section presents and discusses the results; and the final section, "Conclusions" section concludes by outlining a way forward.

## Study area and data

### Data

A significant portion of the cultivated area in eastern India is rainfed (~75%) [30] and experience relatively more frequent weather shocks, mainly floods, droughts, and cyclones [31]. Data were collected from 48 randomly selected administrative units (districts) from four major rice-growing states of the region: Bihar, Odisha, Uttar Pradesh, and West Bengal. Using remote-sensing data, all villages in the selected districts were classified into stress-prone and non-stress villages (Fig. 1). In each selected district, seven to eight villages were randomly selected from the village census data of 2011, totaling 348 villages. Villages in each district were selected to ensure that 70% were stress-prone and 30% were not. A total of 3517 farmers were interviewed from the 348 selected villages in the year 2017. Using a Computer-Assisted Personal Interviewing (CAPI) tool (surveybe), a comprehensive household survey followed by a risk elicitation experiment was conducted with the sample farmers. The primary survey included modules on household demographic and socioeconomic aspects, landholdings and other assets, risk exposure, input application, agricultural technology adoption, and production aspects.

Existing evidence from risk attitude elicitation experiments shows that factors such as demographic and socioeconomic conditions, emotions and subjective feelings, health, and other indicators influence risk attitude [32–38]. A section of the literature indicates that socioeconomic and demographic indicators such as age, education, household size, gender, wealth, and income have either a positive or no influence on risk aversion [20, 32, 39–42]. Other researchers found a negative influence of some of these factors [33, 41, 43, 44]. Additionally, we collected information on input and output market access, farming experience, liquidity asset holdings, and ethnicity, which could also influence farmers' risk attitude.

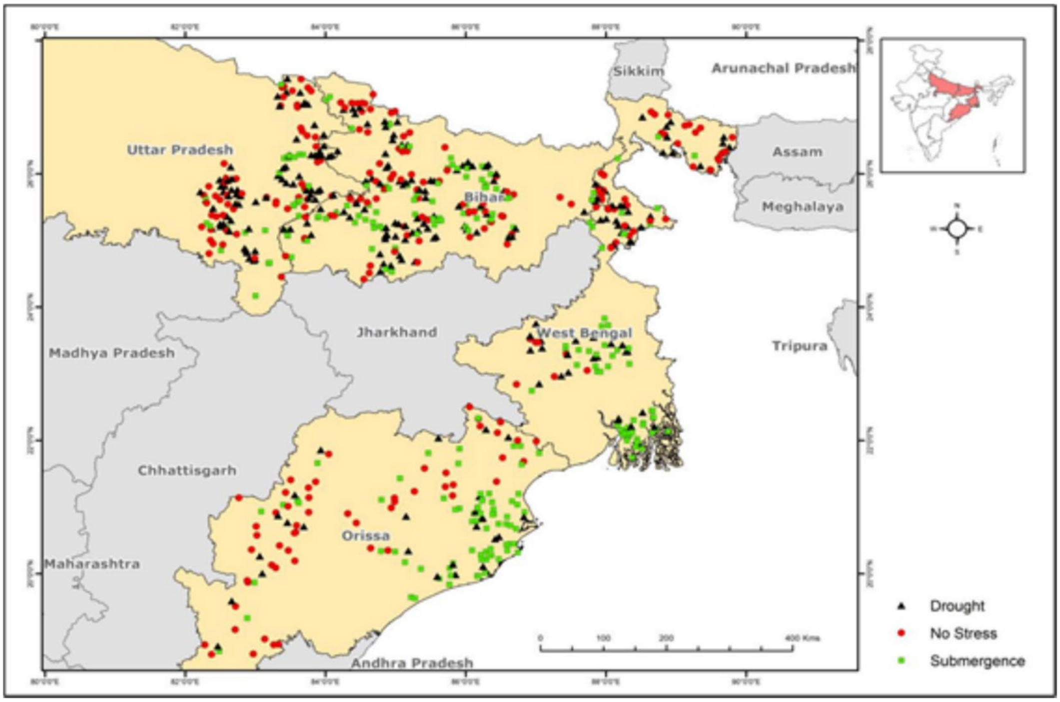


**Fig. 1** Map of the study area indicating the sample points

## Research design

### Risk elicitation

Although other multiple price list-based tasks collect more data from the individuals and produces a more refined estimate of the relevant expected utility function parameters, they are found to be complex and often produce noisier results, especially in the context of lower mathematical abilities [45–47]. In this study, we adopted a simple, easy to comprehend method of eliciting risk attitude developed by Eckel and Grossman [47, 48]. Risk-neutral or risk-seeking individuals opt for a high-risk, high return gamble, while risk-averse individuals choose a lower-risk, lower-return gamble under expected utility theory (EUT) [49]. Initial gambles are designed to require more risk aversion [47, 48]. This method is more appropriate in the context of rural households in developing countries and produces significantly less noisy estimates, particularly where participants have limited cognitive abilities [46]. Risk attitudes elicited by this method are found to be consistent with other widely used methods [49, 50]. In the experiment, we framed individual decisions as simple choices with two alternative payoffs.

Participation in the experiment was made voluntary. Conditional on their decision to participate, participants were asked to choose their most preferred option from a list of five. Each choice option had two possible outcomes with different payoffs, but an equal likelihood of occurrence (50%). Table 1 presents the set of choices and payoff details of their outcomes. Although experiments with real payoffs are found to be effective in eliciting risk attitudes as compared to hypothetical scenarios, a majority of incentivized cases provide an initial endowment to play the game. However, such provisions may induce bias due to the "house money" effect.[1] Therefore, we introduced real payoffs aligned with the experiment, which elicit farmers' risk attitudes close to their actual risk attitude. The payoff amount depends on farmers' decisions on risk attitude and the outcome of a risk event introduced through a roll of a die. As the standard deviation is set to increase linearly from choice-1 to choice-5, indicating an increase in risk, the choice selected is then used as the measure of risk attitude. All payoffs are designed in such a way that the maximum payoff one can receive is INR 180 and the least possible payoff is INR 0.[2]

#### *The experiment*

After the survey, the experimenters read the instructions and provided detailed explanations to farmers regarding the elicitation of risk attitudes. This included eliciting

[1] Often in experiments, subjects are given some initial endowments to play the game, which they may not feel to be their own money, and they make riskier choices than they would if playing with their own money, which is termed a house money effect (47).

[2] The net gain in case of maximum payoff and net loss in case of worst payoff are INR 160 and INR 0, respectively.

**Table 1** Choice options with associated payoffs and risk

| S. N | Choice | Event | Probability | Payoff (INR) | Expected payoff (INR) | Risk* | CRRA** | Risk aversion category |
|---|---|---|---|---|---|---|---|---|
| 1 | Choice_1 | – | – | 40 | 40 | 0.00 | $2 < r$ | Highly risk averse |
| 2 | Choice_2 | A (loss) | 0.5 | 30 | 45 | 10.60 | $1.2 < r < 2$ | Medium risk aversion |
| | | B (gain) | 0.5 | 60 | | | | |
| 3 | Choice_3 | A (loss) | 0.5 | 20 | 60 | 28.30 | $0.67 < r < 1.2$ | Low risk averse |
| | | B (gain) | 0.5 | 100 | | | | |
| 4 | Choice_4 | A (loss) | 0.5 | 10 | 75 | 46.00 | $0.35 < r < 0.67$ | Medium risk seeking |
| | | B (gain) | 0.5 | 140 | | | | |
| 5 | Choice_5 | A (loss) | 0.5 | 00 | 90 | 63.60 | $r < 0.35$ | Highly risk seeking |
| | | B (gain) | 0.5 | 180 | | | | |

*Measured as standard deviation of expected payoff; **Calculated as the range of r (the coefficient of relative risk aversion) in the function $U(X) = X^{(1-r)}/(1-r)$

all the choices, their respective outcomes and payoffs, and potential earnings. To ensure clarity and informed decision-making, visual posters depicting the payoffs of alternative outcomes of all choices were utilized during the explanation process. Once the farmers had a clear understanding of the experiment, they were asked if they were willing to participate. Those who agreed to participate were then prompted to select their most preferred choice from the set. After making a selection, farmers were instructed to roll a six-sided die to determine one of the two outcomes associated with their choice—odd numbers represented outcome A (loss), while even numbers represented outcome B (gain). If Choice_1 is chosen, farmers were not required to roll the die, as the option indicated high level of risk aversion, and they received a payment of INR 40. As shown in Table 1, farmers were paid earnings based on the outcome of their chosen option. In addition, farmers were given the option to opt out the participation.

## Econometric specification

### *Modeling risk attitude*

In the risk elicitation experiment, we considered that farmers made two decisions: first, a participation decision (opt-out); second, a choice of risk options (as indicated by Choice_1 to Choice_5 in Table 1). In addition, the collected dataset features a discrete ordered outcome, but with zero inflated. The high prevalence of zeros can be attributed to three distinct sources: (1) farmers exhibiting very high risk aversion; (2) cultural or religious beliefs influencing farmers to opt out of playing risk games with a payoff; or (3) farmers not understanding the game. Unlike conventional ordered probit models, a zero inflated ordered probit (ZIOP) model can handle such datasets and produce efficient results [51]. Following Greene [52], the ZIOP model splits into two latent equations: a probit selection equation for the participation decision and an ordered probit equation for risk choice conditional on passing the first hurdle of participation. Letting $d_i$ denote a binary decision of farmer i to participate in the risk game or not, the probit model is represented as:

$$d_i^* = \alpha' x_i + \varepsilon_i, d_i = 1(d_i^* > 0) \quad (1)$$

where the latent variable $d_i^*$ represents the propensity for participation in the risk game and is observed in a discrete binary form, where $d_i = 1$ for $d_i^* > 1$ and $d_i = 0$ for $d_i^* \leq 1$. $x_i$ denotes the covariates that affect the decision to participate in the risk game and $\alpha$ is a vector of coefficients to be estimated. The major covariates considered in our model that influence farmers' participation in the game are income, employment, caste, religion and other socio-economic variables. $\varepsilon_i$ is a standard normally distributed residual term.

Next, conditional on the fact that a farmer participates in the game ($d_i = 1$), the level of risk choice is represented by a latent variable, $R_i^{'*}$, which is observed in a discrete form, $R_i'(= 1,2,..,j, wherej = 5)$, and estimated by the ordered probit model in ZIOP, that is, the risk choice is

$$R_i^{'*} = \beta' z_i + u_i \quad (2)$$

where $R_i = \{0 if R_i^{'*} \leq 0 1 if 0 < R_i^{'*} \leq \tau_1 2 if \tau_1 < R_i^{'*} \leq \tau_2 \ldots\ldots\ldots. j if \tau_{j-1} < R_i^{'*} \leq \tau_j$

where z is a vector of explanatory variables that influence farmers' risk choice with coefficients β, u is a standard normal error term, and $\tau_2$ represents boundary parameters.

In ZIOP, the decision to participate and the level of risk choice are considered jointly. $R_i^* = d_i R'^*_i$, that is, to observe positive values for the latent variable of risk choice ($R_i^*$), participation has to be 1 (a joint requirement of $d_i = 1$ and $R'^*_i > 0$). $R^*_i = 0$ if either $d_i = 0$ or $R'^*_i = 0$. The joint probabilities in the ordered ZIOP model can be written as

$$PrPr(R^*_i = 0|x_i, z_i) = \left[1 - \Phi\left(\alpha' x_i\right)\right] + \Phi\left(\alpha' x_i\right)\Phi\left(-\beta' z_i\right) \quad (3)$$

and

$$PrPr(R^*_i = j|x_i, z_i) = \Phi\left(\alpha' x_i\right)\left[\Phi\left(\tau_j - \beta' z_i\right) - \Phi\left(\tau_{j-1} - \beta' z_i\right)\right] \quad (4)$$

The high incidence of zeros captured in Eq. (5) is due to an inflation of the probability of non-participation in the risk game and the joint probability of the risk choice to participate in the game but with an intensity of zero. Equation (6) indicates the probability that $R^*_i$ takes a particular risk level, on the interval differences in the probability density for the discrete outcomes, but also jointly with the probability that $d_i = 1$.

### *Risk attitude, adoption of technology, and productivity impacts*

Farmers' decision on adopting agricultural technology depends on the expected incremental benefits of the technology under various risk scenarios (after accounting for the total costs associated with the shift to the new technology, including transaction and information costs). However, the expected incremental benefits from the adoption are unknown, which can be expressed as a function of the farmers' observed characteristics and attributes of the adoption. Let $\widehat{EB}_{iT}$ be a latent variable representing the expected incremental benefits from the adoption of technology T.

$$\widehat{EB}_{iT} = \xi R_i + \gamma M_i + \nu_i, \text{where } EB_{iT} = \{1\, if\, \widehat{EB}_{iT} > 0\, 0\, if\, \widehat{EB}_{iT} \leq 0 \quad (5)$$

where $M$ is a vector of factors that influence farmers' decision to adopt the improved agricultural technology T, $\gamma$ denotes a vector of parameters to be estimated, $\xi$ is the coefficient of risk attitude ($R$), and $\nu$ is the error term, assumed to be standard normally distributed. If $\widehat{EB}_1 > 0$, the expected benefit of adopting the technology is greater than non-adoption, leading to an adoption decision ($A_i = 1$).

In the next stage, we demonstrate the importance of risk attitude in the adoption of improved agricultural technology and consequent impact of the adoption on productivity. We use a two-stage approach to estimate the impacts: (1) the adoption of technologies (here, mechanization and stress tolerant rice seeds) which is having suspected endogenous issues due to selection bias owing to unobserved heterogeneities, and (2) impacts of adoption on rice productivity. By employing Endogenous Switching Regression (ESR), we simultaneously fit both the selection and outcome equations using full information maximum likelihood method [53]. The outcome function, the effect of adoption on rice productivity, is expressed as follows:

$$P_i = f(A, X, S, \beta) + \varepsilon \quad (6)$$

where $P$ is the natural log transformed quantity of rice produced per acre (in quintal)[3], $A$ indicates adoption status (1 if a farmer adopted a particular improved practice and 0 if not adopted), $X$ is a vector of input variables (fertilizer, labor, irrigation, and landholding), $S$ is a vector of socioeconomic variables, and β and ε refer to a vector of parameters to be estimated and the error term, respectively. Conditional on adoption and non-adoption decisions, their outcome functions are specified as an ESR model as follows:

$$Regime1 : P_{Ai} = \beta_A X_{Ai} + \varepsilon_{Ai}\ ifA_i = 1 \quad (7)$$

$$Regime2 : P_{NAi} = \beta_{NA} X_{NAi} + \varepsilon_{NAi}\ ifA_i = 0 \quad (8)$$

where $P_{Ai}$ and $P_{NAi}$ is the natural log transformed rice productivity of adopters and non-adopters, respectively, $\beta_A$ and $\beta_{NA}$ are vectors of parameters to be estimated for regime 1 and 2, respectively, and $\varepsilon_A$ and $\varepsilon_{NA}$ are the error terms of the respective regimes. Since the adoption of improved practices is endogenous, employing ESR requires an instrument(s) in the selection equation (Eq. 5) that influences the adoption decision but not the outcome indicators.

Using ESR estimates, conditional expectations are calculated as follows:

The expected rice productivity of adopters:

$$E(A_i = 1, x_{Ai}) = X_i\beta_A + \sigma_A\rho_A \quad (9)$$

The expected rice productivity of non-adopters:

$$E(A_i = 0, x_{NAi}) = X_i\beta_{NA} + \sigma_{NA}\rho_{NA} \quad (10)$$

[3] 1 acre = 0.4047 hectare and 1 quintal = 0.1 metric tonne.

The expected rice productivity of adopters had they chosen not to adopt:

$$E(A_i = 1, x_{NAi}) = X_i\beta_{NA} + \sigma_{NA}\rho_A \quad (11)$$

The expected rice productivity of non-adopters had they chosen to adopt:

$$E(A_i = 0, x_{Ai}) = X_i\beta_A + \sigma_A\rho_{NA} \quad (12)$$

Using these conditional expectations, the average treatment on treated (ATT) (difference between Eqs. 9 and 11) and average treatment on untreated (ATU) (difference between Eqs. 10 and 12) can be estimated as follows:

$$ATT = E(A_i = 1, x_{Ai}) - E(A_i = 1, x_{NAi}) \quad (13)$$

$$ATU = E(A_i = 0, x_{Ai}) - E(A_i = 0, x_{NAi}) \quad (14)$$

Identification of instrument:

In the literature, factors such as climate information, climate belief, adaptation belief [10], caste [11], willingness to try new technologies [54], demonstration trials and field days [55], and perception about the technologies [55] are considered instrumental in the adoption of technologies. We examined the potential of the farmers' risk attitude as an instrument as this factor has a causal pathway only through the adoption of technologies, with no direct impact on productivity. We, therefore, assessed the effect of risk attitude on the adoption of improved agricultural practices such as mechanization and stress-tolerant rice varieties (STRVs), and impact of the adoption on rice productivity. We tested the validity of this instrument for our models using a falsification test [56] and the parameter estimates used for the same are presented in Appendix Tables 8 and 9. The instrument (risk attitude) is found to be valid for our models, as it significantly influenced the adoption of mechanization and STRVs, but it did not influence the rice productivity (outcome variable) of non-adopters of these technologies.

## Results and discussion

### Descriptive statistics

Table 2 presents descriptive statistics of the outcome and predictor variables, which include important socioeconomic characteristics of the farmers, inputs, and other factors that could influence farmers' risk attitude, adoption of technologies, and rice productivity. On average, farmers' land and livestock holdings were 2.21 acres[4] and around five animals, respectively. Most household heads were male (98%) and older adults (average age was 53 years) with an average education of six years. On average, households had five members. Sample farmers belonged to four main caste categories: General Caste (34%), Scheduled Caste (SC) (23%), Scheduled Tribes (ST) (12%), and Other Backward Classes (OBC) (31%).

The average distance from input and output markets was 3.44 km and 3.61 km, respectively. Approximately 65% of households identified agriculture and allied activities as their primary occupation. The majority of households belonged to the Hindu religion (88%), followed by Muslim (11%), with the reminder belonged to other religions. Since farmers belonging to Christian and other religions constituted less than 1% of the sample, we grouped them with the Hindu category and made the religion variable binary (=0 if Others and = 1 if Muslim).

Figure 2 presents details of farmers' risk attitudes. Approximately 29% of the sample farmers opted out of participating in the experiment, possibly due to either very high risk aversion or cultural and other considerations. Around 35% of the farmers chose the first two options (Option_0 and Option_1), indicating high risk aversion. Approximately 36% of the farmers opted for Option_2 and Option_3, indicating moderate risk aversion, while about 29% of the farmers selected high risk-seeking / risk neutral options (_4 and _5). Contrary to the literature, these results indicate that farmers' risk attitudes were heterogeneous. The factors influencing such heterogenous risk attitudes and their effects on technology adoption decisions are presented in the rest of this section.

### Farmers' risk attitude

Results from the ZIOP model for the participation decision and risk attitude variables are presented in Table 3. The estimates of levels of risk options are conditional on participation in the experiment. Livestock holdings (LIVESTOCK_HOLDINGS) and education level (HH_EDUCATION) significantly and negatively influenced the participation decision, while positively influencing risk attitude conditional on participation. This suggests that liquid asset holdings have a direct bearing on risk attitude because liquid assets serve as buffer stock that can be liquidated in the event of risks to smooth consumption. Respondents' age (HH_AGE) did not influence the participation decision, whereas, it negatively influenced risk attitude, indicating that young farmers were relatively more risk seeking than older farmers. An increase in household size (HH_SIZE) increases the likelihood of participation in the experiment, likely due to the diverse income sources of larger households. However, household size did not influence the respondents' attitude over risk options, contrary to the findings of Saqib [41]. The results indicate that household size has heterogenous

[4] Which indicates that a majority of the farmers are holding marginal landholdings as per the Government of India classification of farmers based on the size of landholding (less than 2.5 acre (1 hectare)).

**Table 2** Descriptive statistics of the variables

| Variable | Description | Full sample (N = 2875) | Mechanization | | | STRV | | |
|---|---|---|---|---|---|---|---|---|
| | | | Adopters (N = 1585) | Non-adopters (N = 1290) | Mean difference | Adopters (*N* = 797) | Non-adopters (*N* = 443) | Mean difference |
| RICE_PRODUCTIVITY | Rice productivity (quintals/acre) | 13.179 | 14.689 | 11.323 | 3.365*** | 13.660 | 13.600 | 0.060 |
| LAND_HOLDING | Household's own landholding (acres) | 2.212 | 2.780 | 1.514 | 1.266 | 1.693 | 1.821 | -0.128 |
| LIVESTOCK_HOLDINGS | Total number of livestock owned by household (count) | 4.923 | 4.615 | 5.302 | – 0.687 | 5.447 | 3.957 | 1.490 |
| HH_EDUCATION | Education of the household head (years) | 6.284 | 7.015 | 5.386 | 1.629 | 6.148 | 6.679 | – 0.531 |
| HH_AGE | Age of the household head (years) | 52.663 | 53.013 | 52.232 | 0.781 | 50.824 | 54.756 | – 3.932 |
| HH_SIZE | Household size (count) | 5.094 | 5.287 | 4.856 | 0.431 | 4.588 | 5.104 | – 0.515 |
| HH_GENDER | Household head's gender (= 1 if female and = 0 if male) | 0.025 | 0.025 | 0.024 | 0.001 | 0.023 | 0.020 | 0.002 |
| CASTE_CATEGORY | Caste category (1 = General, 2 = SC, 3 = ST, and 4 = OBC) | 2.712 | 2.415 | 3.078 | – 0.662 | 1.704 | 2.298 | – 0.594 |
| DIST_INPUTM | Distance from house to the nearest input market (km) | 3.440 | 3.137 | 3.811 | – 0.674 | 2.583 | 3.270 | – 0.686 |
| DIST_OUTPUTM | Distance from house to the nearest output market (km) | 3.608 | 3.471 | 3.778 | – 0.307 | 2.766 | 3.278 | – 0.512 |
| PRIM_OCCU | Primary occupation of household head (= 1 if agriculture & allied and 0 if others) | 0.648 | 0.682 | 0.605 | 0.077 | 0.615 | 0.648 | – 0.033 |
| RELIGION | Religion (= 1 if Muslim and = 0 if others) | 0.106 | 0.139 | 0.065 | 0.074 | 0.207 | 0.061 | 0.146 |
| IRRIGATION_PERCENT | Percent of land under irrigation (%) | 52.759 | 69.639 | 32.019 | 37.620 | 52.993 | 47.473 | 5.520 |
| RISK_PREF_BIN | Risk attitude (= 1 if risk seeking and 0 if risk averse) | 0.513 | 0.531 | 0.492 | 0.038 | 0.620 | 0.535 | 0.085 |
| TOTAL_FEMALE_HOURS | No. of woman labour-days applied per acre | 24.71 | 25.87 | 23.29 | 2.58* | 20.13 | 15.52 | 4.612*** |
| TOTAL_MALE_HOURS | No. of man labour-days applied per acre | 73.65 | 78.84 | 67.28 | 11.56*** | 85.01 | 75.19 | 9.822** |
| CHEM_FERTILIZER | Total quantity of chemical fertilizer applied (kg per acre) | 106.09 | 126.34 | 81.21 | 45.13*** | 89.72 | 89.41 | 0.306 |

The values displayed for t-tests are the differences in the means across the groups; ***, **, and * indicate significance at the 1, 5, and 10% critical level

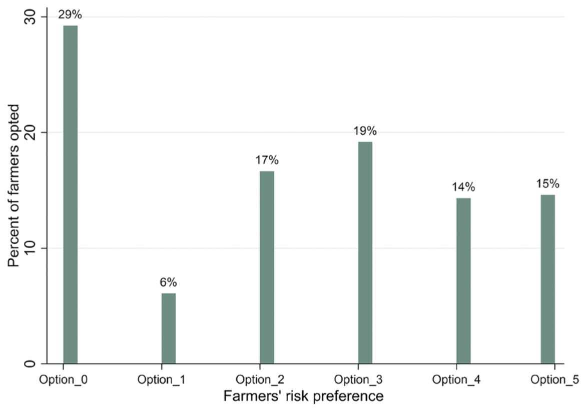


**Fig. 2** Summary of frequencies of risk attitude

/ no effect on risk attitude. Overall, respondents predominantly belonged to Scheduled Tribes and Castes, and Other Backward Classes (CASTE_CATEGORY_SC, _ST, and _OBC) were more likely to choose risk-averse options than those who belonged to the General Caste. Farmers having primary occupations (PRIM_OCCU) other than agriculture were less likely to participate than those whose primary occupation was agriculture. Similarly, an increase in distance to the input market (DIST_INPUTM) has a negative influence on the participation decision, indicating that poor market access could directly influence farmers' risk aversion.

Unlike in linear regression models, individual coefficients of ZIOP model do not convey information on the magnitude of the effect on dependent variables for an infinitely small/unit change in explanatory variables. Hence, the marginal effects of explanatory variables at sample means are estimated to interpret the likelihood of risk levels, presented in Appendix Table 10. The probability of choosing a highly risk-averse option (Option_1) is presented in the ME_1 column, which is significantly influenced by livestock holdings, education, age, caste category (SC and ST), distance to input market, primary occupation, and prone to risks. An increase in a year of education decreased probability of high risk averse by 0.002. The probability increased by 0.0004 for each additional year of age. The probabilities that farmers belonging to SC and other castes choose highly risk-averse options rose by 0.014 and 0.042, respectively, vis-à-vis those belonging to the General Caste category. Similarly, marginal effects for other options are presented in ME_2, ME_3, ME_4, and ME_5 for options 2 (medium risk averse), 3 (low risk averse), 4 (medium risk taking), and 5 (high risk taking), respectively.

Overall results show the likelihood of choosing the options associated with risk seeking increased with an increase in liquid asset holdings and education.

**Table 3** Zero-inflated ordered probit model (Obs. = 3517; Wald chi-square [18] = 87.32; Prob > $\chi^2$ = 0.000)

| Variables | Participation_probit | Risk_ attitude (Oprobit) |
|---|---|---|
| LAND_HOLDING | – 0.010 | 0.007 |
| | (0.009) | (0.007) |
| LIVESTOCK_HOLDINGS | – 0.019*** | 0.017*** |
| | (0.006) | (0.004) |
| HH_EDUCATION | – 0.049*** | 0.025*** |
| | (0.012) | (0.006) |
| HH_AGE | 0.000 | – 0.007*** |
| | (0.004) | (0.002) |
| HH_SIZE | 0.071*** | 0.001 |
| | (0.026) | (0.011) |
| CASTE_CATEGORY_SC | 0.467** | – 0.182*** |
| | (0.229) | (0.061) |
| CASTE_CATEGORY_ST | – 0.377** | – 0.294*** |
| | (0.168) | (0.092) |
| CASTE_CATEGORY_OBC | – 0.743*** | 0.026 |
| | (0.124) | (0.063) |
| CASTE_CATEGORY_Other | 3.725 | – 0.761*** |
| | (181.8) | (0.267) |
| DIST_INPUTM | – 0.026* | – 0.001 |
| | (0.014) | (0.010) |
| DIST_OUTPUTM | 0.002 | 0.002 |
| | (0.011) | (0.006) |
| PRIM_OCCU_Labor | – 0.065 | 0.007 |
| | (0.150) | (0.070) |
| PRIM_OCCU_ Other | – 0.731*** | 0.168 |
| | (0.161) | (0.111) |
| PRIM_OCCU_Salaried Employment | 0.018 | – 0.162 |
| | (0.208) | (0.125) |
| PRIM_OCCU_Self-Employment | 0.221 | – 0.111 |
| | (0.155) | (0.069) |
| RELIGION_Muslim | 1.225** | |
| | (0.520) | |
| Constant | 1.462*** | |
| | (0.289) | |

Standard errors in parentheses; ****p* <0.01, ***p* <0.05, **p* <0.1; base categories: General – CASTE_CATEGORY, Agriculture – PRIM_OCCU, Others – RELIGION

Education estimates contradict a study conducted in Mozambique [33, 41]. The age of the respondents has a negative effect on choosing options associated with risk seeking behavior, which aligns with the findings of some literature [36, 57, 58], but contradict the findings of De Brauw and Eozenou [33], which indicate younger respondents are more risk averse than those between 30 and 50 years old. Farmers belonging to a minority caste/social class (SC and ST) were more likely to choose options associated with risk aversion than those belonging to the upper caste. Farmers whose primary occupation was other than agriculture were less likely to choose risk-averse options, which aligns with Roe [36]. The following section discusses how these heterogeneous risk attitudes could influence farmers' adoption of improved agricultural practices that in turn influences their crop productivity.

### Risk attitude, technology adoption, and productivity gain in rice cultivation

Given the inherent risky nature of agricultural production due to multiple stresses, farmers' risk attitude could be one of the influencing factors associated with their decisions on adopting technological innovations and improved practices in sustainable agricultural development. However, to the best of our knowledge, there is hardly any evidence on this, especially in the Indian context, where small and marginal landholders are predominant. Therefore, we analyzed how farmers' risk attitude influences their decisions on the adoption of improved agricultural technologies and whether their adoption has any impact on productivity improvement in rice cultivation. The literature has established the adoption of improved practices is endogenous for evaluating their impact on yield [10, 11, 56]. To account for this, we used the ESR approach and developed models for testing two technological innovations: (1) mechanization, which is capital intensive, and (2) STRVs, which, unlike mechanization are low-cost but effective against crop loss during climate risks and comes with no yield penalty during normal seasons.

In one model, we tested whether farmers' risk attitude influenced their adoption of mechanization and whether adoption led to a productivity gain in rice production. For the selection equation of the mechanization model, to account for intensity, we considered the number of machinery units used by the farmers in rice production. Thus, we created a binary variable; farmers who adopted more than two machines are considered as adopters, and non-adopters otherwise. In the second, we tested whether risk attitude influenced the adoption of STRVs and whether adoption led to a productivity gain in rice production. In this model, the binary variable of the selection model indicates 1 if an STRV was adopted and 0 otherwise. In addition to these two models, we tested the effect of risk attitude on the farmers' seed replenishment (1 if replenished seeds in the previous season or 0 otherwise). The outcome variable for these models is the natural log of rice productivity in quintals per acre.

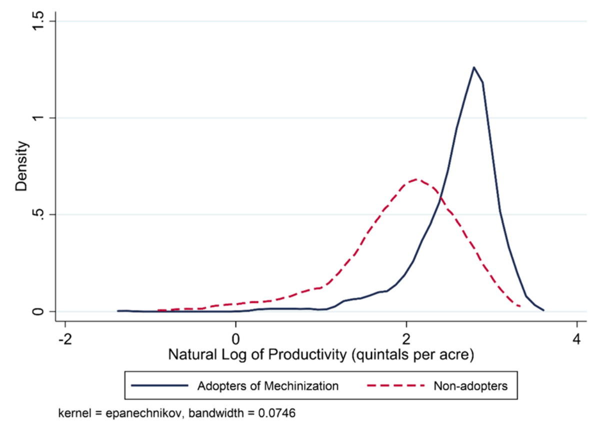


**Fig. 3** Distribution of rice productivity among adopters and non-adopters of mechanization

#### *Influence of risk attitude on the adoption of mechanization and rice productivity*

The average rice productivity of sample farmers was 13.2 quintals per acre, whereas it was 14.69 and 11.32 quintals per acre for mechanized and non-mechanized farmers, respectively. The productivity distribution among mechanized and non-mechanized farmers is presented in Fig. 3, which shows that distribution of rice productivity of non-mechanized farmers is skewed more toward lower productivity than that of mechanized farmers.

Table 4 presents the ESR results for the mechanization model. The significant covariance term for the adopters shows the presence of selection bias. Results of the selection (adoption) equation are presented in the second column, which represents the factors influencing the adoption of mechanization. The results indicate that farmers exhibiting risk-seeking behavior were more likely to adopt mechanization than those who were risk averse. This is a unique and crucial finding, as most machinery comes with a high capital cost, which could have deterred risk-averse farmers from adopting mechanization. This implies that either custom-hiring services should be encouraged to provide low-cost services without capital cost, or joint ownership schemes or farmer producer organizations should be promoted by the government to alleviate the cost burden. Alternatively, a policy toward the development of context specific small-scale machinery could be another feasible solution for widespread adoption.

Other socioeconomic control variables also influenced adoption. The adoption of mechanization is significantly and negatively influenced by an increase in female labor

**Table 4** Estimates of the ESR model for mechanization (=1 if more than 2 machines adopted; =0 if no machines adopted) ($N$=779)

| Variables | Mechanization_ Adoption | Rice productivity (quintals/acre) | |
|---|---|---|---|
| | | Adopters | Non-adopters |
| TOTAL_FEMALE_ HOURS | − 0.004*** | − 0.000 | 0.000 |
| | (0.001) | (0.000) | (0.002) |
| TOTAL_MALE_HOURS | 0.001 | 0.001*** | 0.002 |
| | (0.001) | (0.000) | (0.001) |
| IRRIGATION_PERCENT | 0.008*** | 0.001*** | 0.001 |
| | (0.002) | (0.001) | (0.004) |
| LN_ CHEM_FERTILIZER | 0.560*** | 0.058** | 0.082 |
| | (0.097) | (0.027) | (0.225) |
| LAND_HOLDING | − 0.013 | 0.001 | − 0.124*** |
| | (0.020) | (0.003) | (0.040) |
| HH_AGE | 0.011* | − 0.000 | 0.006 |
| | (0.006) | (0.001) | (0.007) |
| HH_SIZE | 0.0264 | − 0.004 | 0.029 |
| | (0.038) | (0.006) | (0.036) |
| DIST_INPUTM | − 0.027 | 0.000 | − 0.063*** |
| | (0.025) | (0.006) | (0.024) |
| PRIM_OCCU | 0.040 | 0.037 | 0.020 |
| | (0.160) | (0.034) | (0.132) |
| HH_EDUCATION | 0.080*** | 0.015*** | 0.034 |
| | (0.019) | (0.004) | (0.038) |
| RISK_PREF_BIN | 0.258* | | |
| | (0.154) | | |
| Constant | − 2.553*** | 2.083*** | 1.380** |
| | (0.542) | (0.157) | (0.676) |
| lns1 | | − 0.876*** | |
| | | (0.027) | |
| r1 | | − 0.036 | |
| | | (0.183) | |
| lns2 | | | − 0.686*** |
| | | | (0.112) |
| r2 | | | − 0.101 |
| | | | (1.061) |

Standard errors in parentheses; ***$p$ < 0.01, **$p$ < 0.05, *$p$ < 0.1

hours, as major labor activities such as manual transplanting/broadcasting, weeding, and harvesting are usually carried out by female labor. The education coefficient positively and significantly influenced adoption, indicating that educated farmers were more likely to adopt mechanization, possibly due to their access to information and other resources. This result aligns with the literature, which demonstrate that an increase in education increases the likelihood of technology adoption [9, 10, 59, 60]. This implies that, to increase adoption levels, more attention should be given to increasing awareness and adoption literacy. An increase in access to irrigation and input-intensive agricultural practices (chemical fertilizer) significantly and positively led to the adoption of mechanization.

Columns 3 and 4 of Table 4 present the factors influencing the rice productivity of the adopters and non-adopters of mechanization, respectively. The number of man labor hours used, extent of irrigation access, input (chemical fertilizer) application, and education level significantly and positively influenced the rice productivity of mechanized farmers, whereas landholding and distance to the input market significantly and negatively influenced the rice productivity of non-mechanized farmers. For a robustness check, we also ran a simultaneous equation model, three-stage least squares, and the predictors were found to be consistent (Appendix Table 11).

The results in Table 5 indicate that the adoption of mechanization significantly increased average rice productivity by 22%, which aligns with previous literature [11, 12, 28, 61]. Rice productivity would have decreased by 22% if the adopters had not adopted mechanization, whereas the rice productivity of non-adopters would have increased by 37% if they had adopted mechanization. Therefore, the significant increase in rice productivity (ATT) due to mechanization implies food security and contributes to a welfare gain among the adopters. ATU indicates the potential to significantly increase productivity among non-adopters. Appropriate target-oriented policy measures to increase adoption levels could

**Table 5** Mechanization treatment effects on rice productivity (quintals per acre)

| Treatments | To adopt | Not to adopt | Treatment effects | Change |
|---|---|---|---|---|
| Farmers who mechanized | 13.988 (1.968) | 10.903 (4.523) | ATT = 3.084*** (3.956) | 22% |
| Farmers who did not mechanize | 11.785 (1.646) | 8.584 (2.985) | ATU = 3.200*** (2.305) | 37% |

*** Significant at 1% level ($t$-test); standard errors in parentheses

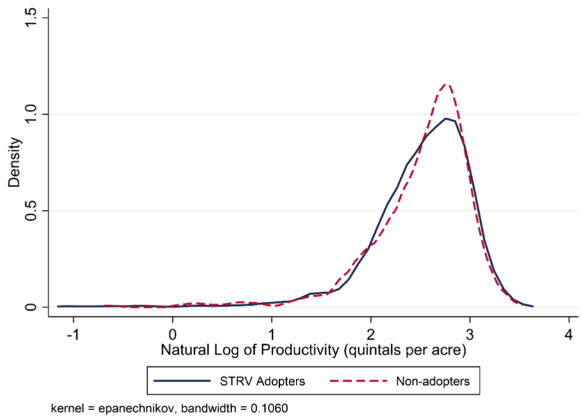


**Fig. 4** Distribution of rice productivity among adopters and non-adopters of STRVs

further contribute to food security and the goal of doubling farmers' income.

### *Influence of risk attitude on the adoption of STRVs and rice productivity*

STRVs are considered one of the promising new technologies for increasing rice production [62]. Therefore, the adoption of STRVs plays a crucial role not only in coping with risks but also in enhancing productivity during normal years by facilitating the crowding-in of other investments [63]. The average rice productivity of STRV adopters was 13.66 quintals per acre, whereas it was 13.60 quintals per acre for non-adopters. Figure 4 presents the productivity distribution among STRV adopters and non-adopters.

Table 6 reports the ESR results of the adoption of STRVs and their impact on rice productivity. The significant covariance term for STRV adopters indicates the presence of selection bias. Results of the selection (adoption) equation are presented in the second column, highlighting the factors influencing the adoption of STRVs. The risk behavior exhibited by the farmers is also a crucial factor in explaining the adoption of STRVs. The results indicate that those who exhibited risk-averse behavior were more likely to adopt STRVs, contradicting with Jianjun [24]. This could be attributed to the potential of STRVs to mitigate low- to medium-range floods/droughts, which are more frequent compared with high-intensity risks. In addition, research evidence indicates a yield advantage in the case of STRV adoption [62] during normal years, with pronounced benefits during low-intensity risk events. The cost factor may not have influenced the adoption decision, as the cost of STRV seeds is generally similar to that of other high-yielding rice varieties. However, anecdotal evidence from the field indicates that farmers were interested in adopting STRVs but faced challenges in accessing the seeds, indicating last-mile

**Table 6** Estimates of the ESR model on STRV adoption (=1 if STRV adopted and 0 otherwise) (N = 1186)

| Variables | STRV_Adoption | Rice productivity (quintals/acre) | |
|---|---|---|---|
| | | Adopters | Non-adopters |
| TOTAL_FEMALE_HOURS | 0.002** | 0.000 | − 0.002** |
| | (0.001) | (0.000) | (0.001) |
| TOTAL_MALE_HOURS | 0.001 | − 0.000 | − 0.000 |
| | (0.001) | (0.000) | (0.000) |
| IRRIGATION_PERCENT | 0.001 | 0.002*** | 0.001 |
| | (0.001) | (0.000) | (0.001) |
| LN_ CHEM_FERTILIZER | − 0.159* | 0.118*** | 0.233*** |
| | (0.085) | (0.029) | (0.053) |
| LAND_HOLDING | 0.057* | 0.003 | − 0.004 |
| | (0.030) | (0.008) | (0.019) |
| HH_AGE | − 0.013*** | 0.000 | − 0.001 |
| | (0.004) | (0.002) | (0.003) |
| HH_SIZE | − 0.062** | − 0.023** | − 0.003 |
| | (0.026) | (0.010) | (0.014) |
| DIST_INPUTM | − 0.056** | 0.007 | − 0.026* |
| | (0.024) | (0.010) | (0.014) |
| PRIM_OCCU | 0.151 | 0.013 | 0.113* |
| | (0.105) | (0.039) | (0.059) |
| HH_EDUCATION | − 0.013 | 0.013*** | − 0.005 |
| | (0.012) | (0.004) | (0.008) |
| RISK_PREF_BIN | − 0.192* | | |
| | (0.102) | | |
| Constant | 2.187*** | 1.919*** | 1.610*** |
| | (0.437) | (0.147) | (0.420) |
| Ins1 | | − 0.901*** | |
| | | (0.032) | |
| r1 | | 0.064 | |
| | | (0.282) | |
| Ins2 | | | − 0.948*** |
| | | | (0.068) |
| r2 | | | − 0.180 |
| | | | (0.369) |

Standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

**Table 7** STRV treatment effects on rice productivity (quintals per acre)

| Treatments | To adopt | Not to adopt | Treatment effects | Change (%) |
|---|---|---|---|---|
| Farmers who adopted STRVs | 12.920 (1.981) | 11.717 (2.276) | ATT = 1.203*** (1.951) | 10 |
| Farmers who did not adopt | 12.298 (1.703) | 13.175 (2.445) | ATU = -0.877*** (2.046) | − 7 |

*** Significant at 1% level (t-test); standard errors in parentheses

delivery problems. Hence, policies aimed at increasing accessibility to and awareness about STRV seeds could enhance adoption level. Furthermore, STRV adoption is significantly and positively influenced by an increase in female labor hours and landholding. However, household size, age of the household head, and distance to the input market significantly and negatively influenced STRV adoption.

The results in columns 3 and 4 of Table 6, respectively, present the factors that influence the rice productivity of the adoption and non-adoption of STRVs. The extent of irrigation access, input (chemical fertilizer) application, and education level significantly and positively influenced the rice productivity of STRV adopters, whereas household size significantly and negatively influenced rice productivity. Input (chemical fertilizer) application and those whose primary occupation was agriculture and allied activities were significantly and positively associated with the rice productivity of STRV non-adopters. For a robustness check, we also ran a simultaneous equation model, three-stage least squares, and the predictors were found to be consistent (Appendix Table 12).

The results in Table 7 indicate that adoption of STRVs significantly increased average rice productivity by 10%. Rice productivity would have decreased by 10% if the adopters had not adopted STRVs. Therefore, the significant increase in rice productivity (ATT) due to STRV adoption implies risk adaptation and food security, contributing to a welfare gain among adopters. If non-adopters of STRVs had adopted them, their rice productivity would have decreased by 7%. This is likely because the yield advantage of STRVs has been proven to be more pronounced in the event of low-intensity risk events than during normal years. These results are consistent with previous studies [62, 64]. Nevertheless, the primary objective of STRVs is to stabilize productivity during stress conditions. Since this technology comes with no capital cost and is priced similar to non-STRV high-yielding variety seeds, it should be extensively disseminated in eastern states where the frequency of low-intensity climate risks is high.

Although it is conventionally recommended to replenish seeds once in three years, seed replenishment every season could significantly influence productivity by maintaining genetic purity and vigor. However, farmers often continue to use seeds saved from previous seasons for more than three years to decapitalize seeds. This has a negative implication for rice productivity [65]. Therefore, the use of certified seeds with the highest genetic purity could contribute to higher yield. To assess the impact of seed replenishment on productivity, we attempted to run an ESR model on seed replenishment during the season when the survey was conducted. However, the model did not converge. In addition, this needs more detailed time series analysis because seeds ideally maintain genetic purity for at least three years, and any change in productivity during this period may not be significant.

## Conclusions

The adoption of improved agricultural practices is vital for coping with multiple stressors and achieving sustainable intensification. However, many of these practices face (s)low adoption rates. Therefore, using primary survey data, this study aims to understand farmers' adoption decisions and their impact on productivity improvement, which may provide policy pointers towards addressing the issue of (s)low adoption. The results indicate that farmers' risk attitudes predominantly skewed toward risk aversion. Those exhibiting a risk-seeking attitude were more likely to adopt mechanization, whereas those with exhibited a risk-averse attitude were more likely to adopt STRVs. Moreover, farmers with a preference for high risk aversion tend to have fewer liquid assets, poor market access, lack of other income sources, lower caste category, and less education, leading to an information deficit. The adoption of mechanization and STRVs has led to improvements in rice productivity. Although rice productivity would have been 7% less if non-adopters had adopted STRVs, the promotion of STRVs is recommended. Beyond enhancing productivity, STRVs help mitigate low to moderate-intensity risks, stabilize productivity in the event of stresses, and incur no capital costs.

In a nutshell, mechanization and STRVs offer complementary benefits for enhancing and stabilizing rice production among farmers. However, these technologies, as our results reveal, are adopted by distinct categories of farmers based on their risk attitudes and that is where scope for policy lies to bridge this gap. To promote the adoption of capital-intensive technologies like mechanization, tailored policies could include incentives for machinery purchases, establishment of custom-hiring services, or collective approaches to provide affordable machinery services. Additionally, developing context-specific small-scale machinery with lower capital costs could facilitate widespread adoption.

On the other hand, scaling the adoption of low-capital-intensive technologies such as STRVs, requires integrating them into both public and private seed systems, coupled with effective information dissemination and awareness campaigns to address farmers' misconceptions or lack of information [15]. These efforts would enable physical and economic access to these technologies, thereby increasing adoption rates and subsequently improving farmers' productivity and income. In many cases, despite possessing knowledge or experience with improved practices, farmers' lack of attention toward them may hinder adoption or optimal utilization of the technologies [66]. Therefore, further research to identify the factors driving farmers' low attention to new and improved practices could inform policy adjustments aimed at enabling farmers to make informed adoption decisions.

## Appendix

See Tables 8, 9, 10, 11 and 12

**Table 8** Parameter estimates for testing the validity of the selection instrument

| Variables | Mechanization (= 1 if adopted more than 2 machines and = 0 if adopted none) (M1) | Log of rice productivity of those who did not adopt mechanization (quintals per acre) (M2) |
|---|---|---|
| RISK_PREF_BIN | 0.326*** (0.086) | − 0.011 (0.139) |
| Constant | − 0.322*** (0.212) | 1.325*** (0.439) |
| Wald test on risky farmers | $X^2 = 139.92$*** | F-stat. = 3.07*** |
| Observations (*N*) | 1039 | 74 |

*M*1: probit model; *M*2: ordinary least squares; standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Parameters for all the other variables are not reported here. The full table is available on request

**Table 9** Parameter estimates for testing the validity of the selection instrument

| Variables | STRV adoption (= 1 if adopted flood-tolerant rice variety and = 0 otherwise) (*M*1) | Log of rice productivity of those who did not adopt STRV (quintals per acre) (*M*2) |
|---|---|---|
| RISK_PREF_BIN | − 0.127# (0.0886) | − 0.018 (0 0.0577) |
| Constant | 0.562*** (0.0666) | 1.773*** (0 0.2671) |
| Wald test on risky farmers | $X^2 = 2.07$# | F-stat. = 4.74*** |
| Observations (N) | 891 | 214 |

*M*1: probit model; *M*2: ordinary least squares; standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Parameters for all the other variables are not reported here. The full table is available on request

**Table 10** Marginal effects for risk levels

| VARIABLES | ME_1 | ME_2 | ME_3 | ME_4 | ME_5 |
|---|---|---|---|---|---|
| LAND_HOLDING | − 0.001 | − 0.001 | − 0.000 | 0.001 | 0.001 |
| | (0.000) | (0.001) | (0.000) | (0.001) | (0.002) |
| LIVESTOCK_HOLDINGS | − 0.001*** | − 0.002*** | − 0.001** | 0.001** | 0.003*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) |
| HH_EDUCATION | − 0.002*** | − 0.004*** | − 0.002*** | 0.001 | 0.004*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| HH_AGE | 0.0003*** | 0.001** | − 0.000 | − 0.001*** | − 0.002*** |
| | (0.0001) | (0.000) | (0.000) | (0.000) | (0.000) |
| HH_SIZE | 0.001 | 0.001* | 0.003*** | 0.003*** | 0.003 |
| | (0.001) | (0.002) | (0.001) | (0.001) | (0.002) |
| CASTE_CATE_SC | 0.014*** | 0.025*** | 0.008* | − 0.009 | − 0.031** |
| | (0.005) | (0.008) | (0.005) | (0.006) | (0.012) |
| CASTE_CATE_ST | 0.009 | 0.004 | − 0.027*** | − 0.042*** | − 0.072*** |
| | (0.006) | (0.011) | (0.007) | (0.008) | (0.015) |
| CASTE_CATE_OBC | − 0.013*** | − 0.034*** | − 0.040*** | − 0.030*** | − 0.030** |
| | (0.004) | (0.008) | (0.006) | (0.005) | (0.012) |
| CASTE_CATE_Others | 0.042*** | 0.042*** | − 0.036 | − 0.071** | − 0.118*** |
| | (0.020) | (0.015) | (0.033) | (0.030) | (0.029) |
| DIST_INPUTM | − 0.000 | − 0.001 | − 0.001* | − 0.001 | − 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) |
| DIST_OUTPUTM | − 0.000 | − 0.000 | 0.000 | 0.000 | 0.001 |
| | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) |
| PRIM_OCCU_Labor | − 0.001 | − 0.003 | − 0.003 | − 0.002 | − 0.001 |
| | (0.005) | (0.009) | (0.006) | (0.006) | (0.013) |
| PRIM_OCCU_ Others | − 0.019*** | − 0.046*** | − 0.040*** | − 0.021*** | − 0.004 |
| | (0.007) | (0.014) | (0.010) | (0.008) | (0.019) |
| PRIM_OCCU_Salaried Employment | 0.008 | 0.011 | − 0.005 | − 0.015 | − 0.032 |
| | (0.008) | (0.012) | (0.008) | (0.011) | (0.021) |
| PRIM_OCCU_Self-Employment | 0.008* | 0.015* | 0.005 | − 0.004 | − 0.016 |
| | (0.005) | (0.008) | (0.005) | (0.007) | (0.013) |
| Observations | 3517 | 3517 | 3517 | 3517 | 3517 |

Standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; marginal effects for categorical variables are the discrete change from the base level

**Table 11** Estimates of three-stage least squares model for mechanization

| Variables | Risk_Attitude | Mechanization | Productivity |
|---|---|---|---|
| RISK_PREF_BIN | | 0.042** | |
| | | (0.020) | |
| MECH_BINARY | | | 0.337*** |
| | | | (0.059) |
| TOTAL_FEMALE_HOURS | | − 0.001*** | 0.000 |
| | | (0.000) | (0.000) |
| TOTAL_MALE_HOURS | | 0.000 | 0.001*** |
| | | (0.000) | (0.000) |
| IRRIGATION_PERCENT | | 0.001*** | 0.001*** |
| | | (0.000) | (0.000) |
| LN_CHEMFERTILIZ | | 0.099*** | 0.067*** |
| | | (0.014) | (0.024) |
| LAND_HOLDING_ACRE | 0.003 | − 0.002 | 0.000 |
| | (0.004) | (0.002) | (0.004) |
| LIVESTOCK_HOLDINGS | − 0.003 | | |
| | (0.003) | | |
| HH_EDUCATION | 0.012*** | 0.010*** | 0.016*** |
| | (0.004) | (0.002) | (0.004) |
| HH_AGE | − 0.001 | 0.002* | 0.000 |
| | (0.001) | (0.001) | (0.001) |
| HH_SIZE | 0.001 | 0.002 | − 0.003 |
| | (0.007) | (0.004) | (0.007) |
| DIST_INPUTM | 0.007 | − 0.004 | − 0.006 |
| | (0.006) | (0.003) | (0.006) |
| PRIM_OCCU | 0.028 | 0.008 | 0.039 |
| | (0.037) | (0.020) | (0.033) |
| CASTE_CATEGORY_SC | − 0.095* | | |
| | (0.050) | | |
| CASTE_CATEGORY_ST | − 0.029 | | |
| | (0.076) | | |
| CASTE_CATEGORY_OBC | 0.044 | | |
| | (0.044) | | |
| RELIGION_Muslim | − 0.025 | | |
| | (0.052) | | |
| bmConstant | 0.548*** | 0.225*** | 1.656*** |
| | (0.100) | (0.075) | (0.124) |
| Observations | 779 | 779 | 779 |
| R-squared | 0.035 | 0.195 | 0.205 |

Standard errors in parentheses; ***$p$ <0.01, **$p$ <0.05, *$p$ <0.1; General Caste is the base category for the CASTE_CATEGORY variable, Occupation other than agriculture for PRIM_OCCU, and Religion other than Muslim for RELIGION

**Table 12** Estimates of three-stage least squares model for STRV

| Variables | Risk_Attitude | STRV | Productivity |
|---|---|---|---|
| RISK_PREF_BIN | | − 0.087*** | |
| | | (0.033) | |
| STRV | | | − 0.016 |
| | | | (0.034) |
| TOTAL_FEMALE_HOURS | | 0.001* | − 0.000 |
| | | (0.000) | (0.000) |
| TOTAL_MALE_HOURS | | 0.000 | − 0.000 |
| | | (0.000) | (0.000) |
| IRRIGATION_PERCENT | | 0.000 | 0.001*** |
| | | (0.000) | (0.000) |
| LN_CHEMFERTILIZ | | − 0.049* | 0.151*** |
| | | (0.027) | (0.025) |
| LAND_HOLDING_ACRE | − 0.001 | 0.015** | 0.000 |
| | (0.008) | (0.008) | (0.007) |
| LIVESTOCK_HOLDINGS | − 0.000 | | |
| | (0.003) | | |
| HH_EDUCATION | 0.013*** | − 0.003 | 0.009** |
| | (0.004) | (0.004) | (0.004) |
| HH_AGE | 0.000 | − 0.004*** | − 0.000 |
| | (0.001) | (0.001) | (0.001) |
| HH_SIZE | 0.004 | − 0.020** | − 0.015** |
| | (0.009) | (0.008) | (0.008) |
| DIST_INPUTM | 0.025*** | − 0.018** | − 0.004 |
| | (0.009) | (0.008) | (0.007) |
| PRIM_OCCU | 0.016 | 0.047 | 0.049 |
| | (0.037) | (0.034) | (0.032) |
| CASTE_CATEGORY_SC | − 0.159*** | | |
| | (0.043) | | |
| CASTE_CATEGORY_ST | − 0.006 | | |
| | (0.094) | | |
| CASTE_CATEGORY_OBC | 0.073 | | |
| | (0.054) | | |
| RELIGION_Muslim | − 0.066 | | |
| | (0.050) | | |
| Constant | 0.446*** | 1.242*** | 1.855*** |
| | (0.101) | (0.135) | (0.131) |
| Observations | 752 | 752 | 752 |
| R-squared | 0.056 | 0.051 | 0.120 |

Standard errors in parentheses; ***$p$ <0.01, **$p$ <0.05, *$p$ <0.1; General Caste is the base category for the CASTE_CATEGORY variable, Occupation other than agriculture for PRIM_OCCU, and Religion other than Muslim for RELIGION

**Abbreviations**

| | |
|---|---|
| ATT | Average treatment on treated |
| ATU | Average treatment on untreated |
| ESR | Endogenous switching regression |
| OBC | Other backward classes |
| SC | Scheduled caste |
| ST | Scheduled tribes |
| STRV | Stress-tolerant varieties |
| ZIOP | Zero inflated ordered probit |

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**Author contributions**
Conceptualization, methodology, investigation, supervision, review and editing were done by PCV. Conceptualization, methodology, investigation, supervision, data curation, analysis, drafting, review and editing were done by VP.

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**Availability of data and materials**
Data will be made available on reasonable request.

## Declarations

**Ethics approval and consent to participate**
As the study involves the primary data collection with farmers, this research has been reviewed and approved by the Ethics Committee of International Rice Research Institute (IRRI) and adheres to the legal requirements of the study country, that is India. Participation in the survey was made completely voluntary and informed consent was taken from all the participant respondents through an informed consent form.

**Consent for publication**
All the primary data have been anonymized. Besides, an informed consent was taken from all the participant respondents through an informed consent form.

**Competing interests**
The authors declare that they have no competing interests.

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## Publisher's Note