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Adapting to Climate Change

The Case of Saline Tolerant Seed Varieties in Coastal Bangladesh

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ABSTRACT

Salt water intrusion and rising soil salnity are threatening food and livelihood security of paddy farmers in coastal Bangladesh. Visible manifestations of these challenges are degraded soils and chronic decline in tradtional farming, as it is becoming an increasingly infeasible means of livelihood. Promoting saline-tolerant paddy varieties (STRV) has been one of the major focuses of the Bangladesh Rice Research Institute (BRRI) and the attention to the problem has been intensified in recent years through a partnerhsip with a consortium of CGIAR centers. However, robust empirical analysis has hitherto been limited. Using farm level data, this paper analyzes the determinants and impacts of the adopting these new varieties. We use a multi-variate logit model to identify the constraints to adoption, and Propensity Score Matching (PSM) and Endogeneous Switching Regression methods to assess the impacts on yeilds, and net income of the paddy farmers. Results show that adopting saline-tolerant rice varieties raises crop yield by an average of 1 to 2 tons per hectare, equivalent to a net income increase of about US$100 per hectare of cultivated land. Yet, adoption rates remain low due to several institutional constraints and perhaps a lack of nudging farmers in the scaling up strategies. Robustness of the results are tested, and the implications are discussed.

Keywords: Technology adoption, salinity intrusion, saline-tolerant seeds, rice cultivation, impact, livelihood, Bangladesh

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ACRONYMS

Acronym	Full form
ATT	Average Treatment Effect on Treated
ATU	Average Treatment Effect on untreated
BARC	Bangladesh Agricultural Research Council
BIHS	Bangladesh Integrated Household Survey
BINA	Bangladesh Institute of Nuclear Agriculture
BRRI	Bangladesh Rice Research Institute
CEM	Coarsened Exact Matching
CGIAR	Consultative Group on International Agricultural Research
CSISA	Cereal System Intensification in South Asia
ESR	Endogenous Switching Regression
FTF	Feed the Future
GoB	Government of Bangladesh
HYV	High yielding varieties
IFPRI	International Food Policy Research Institute
IPCC	Intergovernmental Panel on Climate Change
KBM	Kernel Bandwidth Matching
MIB	Monotonic Imbalance Bounding
NGO	Non-governmental Organizations
NNM	Nearest Neighborhood Matching
PSM	Propensity Score Matching
RCM	Radius Caliper Matching
STRV	Saline-tolerant rice varieties
TH	Heterogeneity effect
TT	Treatment on treated
TU	Treatment on untreated
USAID	United States Agency for International Development
WEAI	Women's Empowerment in Agriculture Index

INTRODUCTION

Salinity intrusion, caused by rising sea levels and declining river flows, is one of the severe environmental factors limiting the productivity of agricultural crops in low income developing countries with long coastlines (Dasgupta et al. 2014, IPCC 2007, Nicollas et al. 2007). The problem is more intense during the dry season, when it is difficult to lower the concentration of salt in surface water due to low rainfall (Baten, Seal, and Lisa 2015). A large body of literature has documented that the rising soil salinity degrades soil and reduces crop yeilds (Parihar et al. 2015; Mikati 1997; Patel et al. 2002; Rogers 2002). It is therefore no surprise that the world's coastal regions are categorized as *extremely vulnerable*, a category that implies that agriculture and people's livelihoods are in danger (IPCC, 2007).

Bangladesh, a low-lying deltaic South Asian country, is highly vulnerable to climate change and the salinity intrusion has been a major national challenge. The coastal households, that largely rely on rice farming, have felt these impacts for decades. Serverity of the problems is evident in publicly available statistics. Coastal zones cover about 20% of the country and 30% of cultivable land; and around 63 % of coastal cultivable lands have been impacted by some degree of salinity over the past 50 years (GoB 2021). Unfortunately, none of the available salt-tolerant rice varieties can produce optimum levels of outputs at the level of salinity that has affected both the soil and groundwater of the coastal districts of Bangladesh (Roy, 2014). Hydrological studies suggest that the groundwater is also turning salty due to salinity intrusion, making crop cultivation unworthwhile for the farmers, and causing farmers to migrate and find alternative livelihoods. This is the central rationale for the government's policy emphasis on developing saline tolerant rice varieties Thus, improving paddy production and productivity is crucial to ensure food security, poverty eradication, and safeguard farmers' livelihoods now and in the future (Ghimire et al. 2015).

Salinity intrusion is a complex problem and varous strategies are being developed to tackle it. Agronomic practices—such as leaching management, alternate rice and shrimp cultivation, conjunctive use of saline and freshwater models, micro-irrigation systems like drip, and regulated surface irrigation systems—are being introduced. The central aims of these strategies are to (i) minimize buildup of salts in the root zone,

(ii) control the salt balance in the soil–water system, and to (iii) minimize the damaging effects of salinity on crop transpiration and soil evaporation (Minhas et al. 2020). However, due to the perceived importance of rice in national food policy, heavey emphasis has been placed on promoting saline tolerant rice varties. The first such variety, called Dyshary BR 23, was introduced in 1988 but has had limited success. So, the breeding pursuits continued and as many as six new varieties have been introduced in the recent decades by the Bangladesh Rice Research Institute (BRRI) in partnership with the CGIAR under a program called Cereal System Intensification in South Asia (CSISA). The latest variety of rice developed by the Bangladesh Rice Resarch Institue (BRRI) and its CGIAR partners can tolerate a high level of salinity and hence there is high level of enthusiasms about the prospect of scaling up this new generation of rice varieties in salinity affected areas. This paper examines the potential and challenges to prmoting these new varieties.

The methods and approaches to analysing the adoption of agricultural techonogies are well established (Becerril and Abdulai 2010; Mendola 2007; Doss and Morris 2000; Besley and Case 1993). In addition to risk and uncertainties, several agroecological, socioeconomic, and cultural factors play important roles in the adoption of new technologies. However, controlling all these factors continues to be a challenge. This is evident in Bangladesh from the fact, adoption rates of saline tolerant varieties remain low, even though all these new varieties have shown high benefit cost ratios in experimental plots (Haque et. al., 2019). The present study attempts to fill this important gap. It undertakes two tasks: (i) it examines socioeconomic and other factors affecting adoption of new varieties and then (ii) estimates the impacts of adoting these varieties on yeild and income of the households. We use a multi-nomial logit regression and Propensity Score Matching (PSM), respectively, to implement our emprical strategy. As robastness check, the impact analysis is also supplemented by Coarsened Exact Method (CEM), and an Endogenous Switching Regression (ESR).

The rest of the paper is organized as follows: the next section provides an overview of data and survey method, which is followed by a decription of methology. Section 4 presents the results and the paper concludes with a summary of results and their implications.

DATA DESCRIPTION

The study relies on the Bangladesh Integrated Household Survey (BIHS), 2015-2016 conducted by the International Food Policy Research Institute (IFPRI). It is the only nationally representative survey in Bangladesh that collects detailed data on (1) plot-level agricultural production and practices, (2) dietary intake of individual household members, (3) anthropometric measurements (height and weight) of all household members, and (4) data to measure women's empowerment in agriculture index (WEAI). A community survey supplements the BIHS data to provide information on area-specific contextual factors. The survey covers 6500 households in 325 primary sampling units. The sample is statistically representative at following levels: (a) nationally representative of rural Bangladesh; (b) representative of rural areas of each of the seven administrative divisions of the country: Barisal, Chittagong, Dhaka, Khulna, Rajshahi, Rangpur, and Sylhet; and (c) representative of the USAID's Feed the Future (FTF) zone of influence.

Table 1. Sample frequency by administrative divisions in Bangladesh affected by salinity

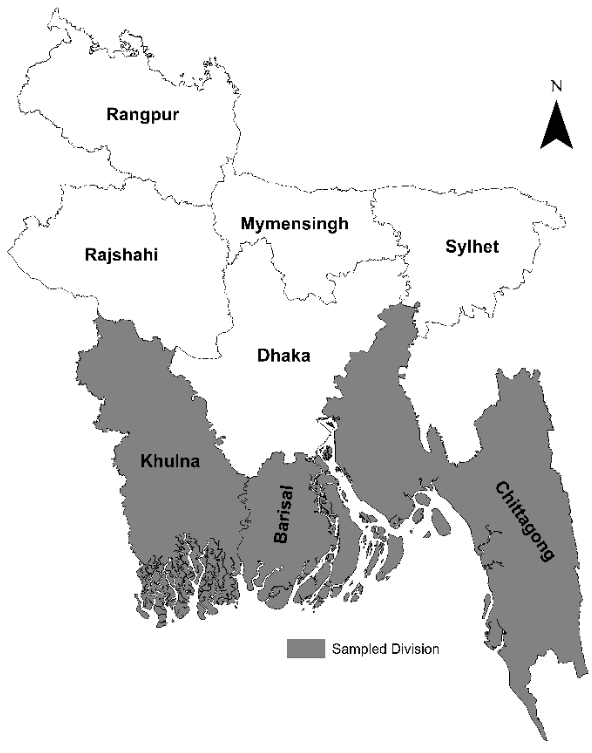
Administrative division	Adopters	Non-adopters	Total
Barisal	210 (14.66)	1222 (85.33)	1432
Chittagong	199 (27.18)	533 (72.81)	732
Khulna	620 (34.85)	1159 (65.15)	1779
Total	1029 (26.10)	2914 (73.91)	3943

Source: Authors' calculations based on BIHS, 2015.
Note: Percent values in parentheses.

For our analysis, the most important section of the survey has been the plot-level information on agricultural practices that provide detailed information about both types and varieties of crops. However, since attributes (saline tolerant, drought tolerant, regular High Yeilding Variety (HYV)) were not collected, we matched the varietal information in the survey with the attributes by variety information data from the Bangladesh Agricultural Research Council (BARC). For example, if a farmer is reported to have cultivated Bangladesh Rice Research Institute (BRRI) Dhan 61 or BINA (Bangladesh Institute of Nuclear Agriculture) Dhan 10, we know from the BARC brochure that these are saline tolerant varieties, with specific information about the level of salinity the variety can tolerate. A list of salinity tolerant paddy seeds is given in the Appendix

1 at the end o this paper. Since the BIHS is representative at the division level, we could select the three divisions - Barisal, Chittagong, and Khulna - that are widely known to be salinity prone (Figure 1).

Figure 1: Salinity prone divisions in Bangladesh



Source: Authors' creation

Of the total BIHS sample of 6500 farm households, 3,950 or about 60% of the total sample are in the three salinity prone divisions, with the smallest number of samples in Chittagong (732) and the largest in Khulna (1779). These numbers are in total conformity with the *a priori* information about the severity of soil salinity severity (IFPRI, 2016).

METHODOLOGICAL FRAMEWORK

Determinants of adoption

Our analysis begins by assessing the key determinants of adoption, which provides important insights about the challenges and opportunities of scaling up this new technology. This is accomplished by estimating a multivariate logit model of the following form:

$$
\begin{aligned}
Y = \ & \beta_0 + \beta_1 age_i + \beta_2 household\ size_i + \beta_3 education_i + \beta_4 subsidy\ card_i \\
& + \beta_5 asset\ index_i + \beta_6 tractor_i + \beta_7 power\ tiller_i + \beta_8 land_i \\
& + \beta_9 gender_i + \beta_{10} pesticide\ dealer_i \\
& + \beta_{11} fertiizer\ dealer_i + \beta_{12} seed\ dealers_i + \beta_{13} urea\ shop_i \\
& + \beta_{14} agriculture\ office_i + \beta_{15} bank_i + \beta_{16} mobile_i + \varepsilon_i
\end{aligned}
\quad (1)
$$

Where Y is the binary dependent variable (adoption = 1, non-adoption = 0), β_0 is the constant term, β_is are the coefficients of the corresponding explanatory variables, and ε_i is the error term. The estimates obtained from logistic regression are expressed on a log-odd scale, which are difficult to interpret. Therefore, marginal value of the coefficients are reported.

Evaluation of impacts

Propensity score matching (PSM)

The impact analysis is carried out using PSM techniques first proposed in Rosenbaum and Rubin (1985). There has been significant extension to this original method in terms of improving the robustness of the estimate. The fundamentals of the model are as follows:

$$E(X) = Pr(T_i == 1 | X_i = x) = E(T_i | X_i = x) \quad (3)$$

where T_i is the binary indicator (T_1 represents adopters, and T_0 represents nonadopters) and X_i is the vector comprising pretreatment covariates including demographic characteristics like age, household size, gender, education, irrigation, access to seed dealers, saving institution, and asset endowments measured by the agricultural implements index and the asset index. The expected value in the above equation is known as the average treatment effect on the treated (ATT), defined by Takahashi & Barrett (2013) as the difference in outcomes in farmer households' net income and crop productivity with or without adoption of saline-tolerant seed varieties.

As a check for robustness, three approaches have been used: kernel bandwidth matching (KBM), nearest neighborhood matching (NNM), and the radius caliper method (RCM). All three methods should yield the same results, but in practice, tradeoffs arise in terms of biases and efficiency pertaining to each method (Caliendo & Kopeining, 2008). We have used all three algorithms to test for robustness of the estimates.

Coarsened exact matching (CEM)

CEM is an alternative to PSM and belongs to the Monotonic Imbalance Bounding (MIB) group (Iacus et al. 2011). This method overcomes one of the shortcomings of PSM in that it restricts the imbalance between the matched and unmatched sample to lie within the ex-ante choice defined by the user. It also ensures that adjusting the imbalance on one variable has no effect on the maximum imbalance of any other variable (Blackwell et al. 2009). Furthermore, the CEM method requires no preconditions about the data generation process, except the usual ignorability assumption. Lacus, King, and Porro (2011) show that CEM is better than other commonly used matching methods in reducing imbalance, model dependence, estimation error bias, variance, and mean. The idea behind CEM is to coarsen each variable by recording in such a way that large identical values are grouped and assigned the same value, followed by the application of the exact matching principle to identify, and remove unmatched units. Lastly, the coarsened data are withdrawn, and original values of the matched data are retained.

After the process of coarsening is completed, CEM creates a set of strata, say, $s \varepsilon S$, each with a few coarsened values of X. Consider a sample of size of n ($n \leq N$) that contains units drawn from population N. Let D_i denote an indicator variable for unit i that takes value 1 if the i^{th} unit belongs to the treatment group and 0 if the i^{th} unit belongs to the control group. The observed outcome variable $Y_i = D_i Y_i (1) + (1-D_i) Y_i$

(0), where $Y_i(0)$ is the outcome for nonadopters of saline-tolerant seed varieties and $Y_i(1)$ is the outcome for adopters. A fixed causal effect is a function of the potential outcome, defined as $Y_i(1) - Y_i(0)$. The estimates for the causal effects on outcome variables, sample average treatment for treated (SATT) can be written as:

$$SATT = \frac{1}{n_T}\sum TE_i \tag{4}$$

where $TE_i = Y_i(1) - Y_i(0) \mid X_i$ and n_T is the total number of treated units in the original sample. The following estimate is valid only if all the treated units are matched. However, when all the units do not match, SATT (sample average treatment for treated) gets transformed into LSATT (local SATT), which can be written mathematically as:

$$LSATT = \frac{1}{m_T}\sum TE_i \tag{5}$$

Where m_t is the number of matched sample units.

Endogenous switching regression (ESR)

For our sample, ESM seems to be appropriate, as we cannot reasonably assume that the set of covariates has the same impact on both groups. ESR addresses the problem of endogeneity by estimating selection and outcome equations separately and simultaneously using a full maximum likelihood estimation method (Wossen et al. 2017; Kumar et al. 2018). The selection equation for adopters can be stated as:

$$Z_i^* = X_i\alpha + \delta_i \; with \; M_i = \begin{cases} 1 \; if \; Z_i^* > 0 \\ 0 \; ; otherwise \end{cases} \tag{6}$$

where X_i represents the vector of explanatory variables comprising sociodemographic details of farmer households. These include age, household size, landholding size, gender, education level, source of irrigation, access to seed dealers, place of savings, the asset index, and the agricultural implements index. The mathematical relationship between independent variables X_i and outcome variable Y can be written as a function of the vector X. A particular household will adopt saline-tolerant seed varieties if $Z_i = 1$ when Y>0, where Y is the outcome generated for adopters in comparison to nonadopters. Therefore, the outcome equations conditional on treatment can be stated as following:

$$\begin{aligned} Regime\ 1: Y_{1i} &= X_{1i} + \mu_{1i}\ if\ Z_i = 1 \\ Regime\ 2: Y_{2i} &= X_{2i} + \mu_{2i}\ if\ Z_i = 0 \end{aligned} \tag{7}$$

Here, μ_{1i} and μ_{2i} are error terms assumed to follow a tri-variate normal distribution with zero mean and covariance. If the estimated covariances between δ and μ's (ρ_1 and ρ_2, respectively) are statistically significant, then adopter households and outcome variables are positively correlated. This model can be used to estimate both ATT and ATU (average treatment effect on untreated), as the model applies a switching regression with correction for selection bias (Maddala & Nelson, 1975).

RESULTS AND DISCUSSION

Descriptive statistics

To provide a broad characterization of adopters and non-adopters, some descriptive analysis of the demographic and household specific economic and social indicators are carried out, and the results are presented in Table 2. The first thing to note from the table is that the study relies on a large sample (3943 households) of which 1029 are adopters of saline tolerant seed varieties and the remaining 2914 are non-adopters. Three sets of descriptive results are worth noting. First, the capital endowment of the farmers - land holding, ownership of agricultural machinery, owning cell phones, and better social capital (e.g., having subsidy cards, being educated, etc.) – appears to be the most significant predictors of adoption. This is consistent with the age-old theory that the relatively richer farmers, who are well-endowed with both physical and social capitals, are generally early adopters since they can bear the risk associated with the new technology.

Second, at a crude level, both yields and income of the adopters are higher than the non-adopters. The average yield per hectare of rice farming is 4.16 tons for the entire sample, with adopter and non-adopters reporting 4.97 tons/hectare and n 3.87 tons/hectare, respectively. The net difference in yield, i.e., 1.09 tons/hectare is significant at 99% level of significance. Finally, the adopters of STRV appear to earn about 23% more returns per unit of land than the non-adopters. The net income from a hectare of rice farming for the entire sample is estimated to be US$249, which compares with US$307 for the adopters and US$229 for non-adopters.

Table 2: Descriptive statistics of key variables

Variables	Sample size (N = 3943)	Adopters (N = 1029)	Non-adopters (N = 2914)	Difference (t-test)
Age (number)	48.20	48.42	48.12	0.29
Household size (number)	4.57	4.62	4.55	0.07
Landholding size (hectare)	0.83	1.03	0.76	0.27***
Asset index	0.44	0.45	0.44	0.01***
Gender (Male = 1, Female = 0)	0.92	0.93	0.91	0.02**
Education				

Variables	Sample size (N = 3943)	Adopters (N = 1029)	Non-adopters (N = 2914)	Difference (t-test)
Illiterate	0.42	0.42	0.42	0.01
Primary and below	0.24	0.21	0.25	-0.04*
Middle and secondary	0.30	0.28	0.30	-0.02
Higher secondary and above	0.04	0.09	0.03	0.06***
Subsidy card (Yes = 1, No = 0)	0.26	0.20	0.28	-0.08***
Tractor (Yes = 1, No = 0)	0.19	0.32	0.15	0.17***
Power tiller (Yes = 1, No = 0)	0.80	0.76	0.82	0.06***
Land (Irrigation= 1, Rainfed= 0)	0.35	0.43	0.32	0.11***
Pesticide dealer (Yes = 1, No = 0)	0.81	0.87	0.79	0.08***
Fertilizer dealer (Yes = 1, No = 0)	0.85	0.87	0.85	0.02*
Seed dealer (Yes = 1, No = 0)	0.68	0.81	0.64	0.17***
Urea shop (Yes = 1, No = 0)	0.08	0.02	0.11	-0.09***
Agriculture office (Yes = 1, No = 0)	0.17	0.18	0.16	0.02
Bank (Yes = 1, No = 0)	0.41	0.52	0.38	0.14***
Mobile (Yes = 1, No = 0)	0.89	0.93	0.89	0.04***
Yield (tons/hectare)	4.16	4.97	3.87	1.09***
Net income (US$/hectare)	249.54	307.01	229.24	77.77***

Source: Authors' calculation based on BIHS survey, 2015–16; *** p<0.01, ** p<0.05, * p<0.1

Determinants of adoption – Logit model

The main purpose of estimating a multivariate logit model has been to assess the predictive power of household specific characteristics on households' adoption decision. Various model specifications were tried, and some key estimates are presented in Table 3. Most results are in conformity with theory and earlier evidence, but some may appear counter intuitive. Asset holding, ownership of agricultural implements (e.g., Tractor and power tiller, etc.) are found to be significant predictors of adoption. Ownership of both power tillers and tractors has positive effects on the adoption of saline tolerant seed varieties. One unit increase in the ownership of power tillers and tractors enhancing the likelihood of adoption by 15 % and 5 %, respectively. Apart from this, the age of the farmers is found to be significant determinates of adoption of STRV. The likelihood of adoption of STRV increases by almost 2% with 1 year increase in the age of the household heads.

There are some counter-intuitive results that call for further discussion. An unusual finding is the insignificance of education in the adoption decision, which is contradictory to recent (Varshney et al. 2022) and earlier literature on the determinants of adoption, especially in the context of green revolution (Hazell et al., 1991; Feder and Umali, 1993). However, the descriptive statistics presented in Table 2 reveals that almost 42% farmers are illiterate in both categories (adopter and non-adopter) of the farmers, and there is no significant variation in terms of middle & secondary level of education. This implies that both adopters and non-adopters in the study region are homogenous in terms of level of education and hence we observe the unusual trend in determining the adoption of STRV. Contrary to earlier studies (Ahmed and Hossain, 1990, and Rashid et al. 2002), female headed households, in this study, appear to be more likely to adopt STRV than the male headed households. The central argument of the earlier studies was that male headed households are better endowed to take more risks and hence higher adoption of risky technologies. While this seems to be an apparent contradiction, one should take note of the fact that the rural Bangladesh has changed dramatically—thanks to large scale NGO movements led by Grameen, BRAC, and others—that resulted in greater women empowerment and better access to credit and extensions services (Develtere & Huybrechts, 2002).

Table 3 also shows significant positive impact of seed dealers in adoption of saline tolerant variety. As observed from Table 3, the increase in access to seed dealers will increase the likelihood of adoption of STRV by 25%.

Table 3: Logit estimates

Variables	**Logit coefficient (Adoption = 1, non-adopter =0)**	**Marginal effect (dy/dx)**
Age	0.157***	0.024***
	(0.023)	(0.004)
Gender (Female = 1, Male = 0)	0.798***	0.123***
	(0.189)	(0.029)
Asset index	2.034***	0.314***
	(0.653)	(0.101)
Education (Base: Illiterate)		
Middle and secondary	-0.087	-0.014
	(0.118)	(0.018)

Variables	Logit coefficient (Adoption = 1, non-adopter =0)	Marginal effect (dy/dx)
Higher secondary and above	0.223	0.035
	(0.181)	(0.028)
Tractor (Yes = 1, No = 0)	0.992***	0.153***
	(0.118)	(0.017)
Power tiller (Yes = 1, No = 0)	0.322**	0.050**
	(0.128)	(0.020)
Bank account (Yes = 1, No = 0)	0.583***	0.090***
	(0.096)	(0.015)
Seed dealer (Yes = 1, No = 0)	1.674***	0.259***
	(0.199)	(0.030)
Agriculture office (Yes = 1, No = 0)	0.444***	0.069***
	(0.133)	(0.020)
Observations	3,943	3,943

Source: Authors' calculations based on BIHS survey, 2015–16; Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1[1]

Impacts of STRV on yield and income

Three sets of estimates on the impacts of STRV on yield and net incomes are generated. The results from the first two sets of estimates (PSM and CEM, respectively) are presented in Table 4. The PSM results, generated using the nearest neighborhood method, show that that both yield and net income of the adopters from per hectare of rice farming are significantly higher than the non-adopters - yields by 1.25 tons/hectare and income by US $95.85 per hectare, respectively. Similar findings have been reported by Islam (2018) and Salam and Sarker (2023) for Bangladesh. The estimates from the CEM method on the same indicators are also similar in magnitudes, with per hectare production and net income of the adopter being higher by 0.92tons/hectare and US$102.02 / hectare, respectively, compared to the non-adopters. These findings are aligned with the results obtained by Pal et. al. (2021) for India, and the results are statistically significant at the 99% level significant and robust to relevant set of specification tests.[2]

[1] Full set of results from the logit analysis will be made available upon request.

[2] The Appendix 2 and 3 provide details of various robustness tests performed to check adequacy of PSM and CEM, respectively.

Table 4: PSM & CEM estimates

Outcome variable	ATT	Standard error
PSM estimates with nearest neighborhood matching		
Yield (tons/hectare)	1.25***	0.19
Net income (US $/hectare)	95.85***	28.25
CEM estimates		
Yield (tons/hectare)	0.92***	0.11
Net income (US $/hectare)	102.02***	29.64

Source: Authors' calculations based on BIHS survey, 2015–16; *** p<0.01

The final set of estimates, presented in Table 5, are based on the ESM method, which is superior to PSM and CEM as it corrects for the sample selectivity bias inherent in the dataset. We can observe from Table 5 that adopters have an average yield of 4.86tons/hectare which would have reduced to 4.01tons/hectare if they hadn't adopted STRV. We also observe that non-adopters have an average yield of 3.62tons/hectare, but the crop yield would have increased to 6.03tons/hectare if they had adopted the technology. The net effect of adoption on the adopters is calculated to be 0.85tons/hectare. This is also known as the treatment on the treated (TT). The net effect of adoption on the non-adopters—known as treatment on the untreated (TU) - is calculated to be 2.41 tons/hectare. The net effect of adoption of STRV, known as heterogeneity effect (TH) is computed to be 1.56 tons/hectare and the estimates are statistically significant. The detailed results are attached in Appendix 4 at the end of this paper.

Table 5: ESR estimates of impacts

Outcome Variables	Adopters	Non-adopters	Treatment effect
Yield (tons/hectare)			
Adopters	4.86	4.01	TT = 0.85***
Non-adopters	6.03	3.62	TU = 2.41***
Heterogeneity effect	BH1 = -1.17 ***	BH2 = 0.39***	TH = -1.56***
Net income (US$/hectare)			
Adopters	531.87	407.75	TT = 124.12***
Non-adopters	478.71	352.76	TU = 125.95***
Heterogeneity effect	BH1 = 52.29***	BH2 = 53.99 ***	TH = -1.83***

Source: BIHS data survey, 2015-16; *** p<0.01, ** p<0.05

Furthermore, Table 5 shows that the adopters have net income of US $ 531.87 /hectare which would have been US $ 407.75 /hectare if they were non-adopters. The net treatment on the treated (TT) is estimated to be US $ 124.12 /hectare. On the contrary, non-adopters have an average income of US $ 352.76/hectare which would have risen to US $ 478.71 /hectare if they had adopted the STVR. The net treatment effect on the untreated (TU) is US$ 125.95/hectare. Finally, the heterogeneity effects, which refers to differences in the outcome due to their inherent differences in skills and human capital (e.g., managerial skills) and experiences in rice farming, are estimated to be small although significant, suggesting that the qualitative differences in our sample of farmers are not large. The estimates obtained from ESR model are similar to the results obtained by Kafando (2023), Pal et al. (2021), and Kumar et., al. (2021, 2020). Details of the estimates are presented in Appendix 5.

For an illustration about the magnitude of overall impacts, consider the following numerical example. Consider the case of increasing STVR adoption rate from 26 percent to 76 percent—that is, pursuing 50% of the non-adopters to adopt STVR. Here is how simple math goes. Bangladesh has a total cultivable land of 8.77 million hectares of which 30 percent (2.63 million ha) are coastal land; and of the coastal land 63 percent (or 1.66 million ha) are salinity affected. Since the adoption rate is 26 percent, the numbers suggest that 1.23 million hectares of coastal land are not cultivated by new generation STVR. Now if only 50% of these lands (1.23/2 =0.613 million or 613,000 ha), were sown with new varieties, net income increase would have increased by roughly US$76.6 million (613,000*125) per cropping season excluding associated multiplier effects of increased value addition, which could be substantive (Diao & Thurlow, 2012).

To summarize, farmers allocating lands to STVR appear to benefit in terms of both yield and per hectare income from rice farming in saline prone districts of the country, and these results hold true under a host of robustness checks. However, these results are at odds with very slow (government began investing in these technologies more than three decades ago) and low adoption rate (26%) of STVR. The government of Bangladesh has invested heavily through its national agriculture research system - notably Bangladesh Rice Research Institute (BRRI) and Bangladesh Institute of Nuclear Agriculture (BINA) - in partnership with the CGIAR's rice center, the International Rice Research Institute (IRRI), as an adaptation measure to climate change in the coastal regions of the country. However, to the best of our knowledge, there has hitherto not been any targeted support to scale up the STVR in coastal Bangladesh - a region that is prominently featured in the National Adaptation Plan and other strategy documents outlining government's plans to increase resilience of the coastal population. Furthermore, earlier generations of STVR have not been as successful in terms of enhancing saline tolerability. As a result, the experiences of the farmers who adopted the earlier varieties might have generated a negative impression about profitability and hence be reluctant to adopt the newer varieties that can withstand higher levels of salinity in the soil.

From a policy standpoint, the central question is whether there should be targeted support for increasing adoption of STVR. Since adoption of these varieties leads to higher return, *laissez-faire* theory would suggest no public intervention. On the other hand, these farmers operate under a host of market failures and hence interventions are justified to incentivize the non-adopters. Large-scale fertilizer subsidies in most of the Asian countries are rationalized on the argument of market failure and national food security. In the case of coastal farming communities, there is an added justification for support, as their livelihood is threatened by the salinity intrusions, resulting in increased livelihood insecurity and out migration which has obvious large scale social costs for the Bangladesh economy.".. However, the support does not need to be in the form of large-scale subsidies, which have been largely agreed to be counterproductive and hence the calls for repurposing fertilizer subsidies are growing louder (UNEP 2021, World Bank 2023).[3]

Empirical behavioral economics offers ideas for how policy might be applied.. The use of the Nudge Theory, advocated by Thale and Sunstein (2008), is being increasingly tested in the context of developing country agriculture. The underlying concept is that farmers' choices can be nudged in a desired direction by taking advantage of farm households' biases through a small, inexpensive intervention to guide their decision. The theory has been empirically tested as a policy instrument in many different contexts. The most widely cited example in the context of agricultural markets is a study by Duflo et al. (2011) in Kenya. The study tested how a nudge can cost-efficiently help Kenyan farmers apply higher level of fertilizer. Their experiment involved offering free delivery if they bought the fertilizer right after harvest, when farmers had more cash at hand. Thus, free delivery of fertilizer is the "nudge" to incentivize farmers to buy

[3] The UN Food System Summit (2021) also highlighted repurposing fertilizer subsidies (Action Track 1)

fertilizer before they run out of cash. This experiment suggested that the farmers in the experiment had increased fertilizer use by 47%–70%.

How such an incentive enhancing experiment can be designed and implemented is beyond the scope of our study, but given growing global experiences, we argue that testing out innovative experiments of such kind will add to knowledge and can potentially inform the government's strategies for scaling up STVR. In addition, much of the coastal region of the country is under the USAID's Feed the Future (FtF) zone of influence and hence provides an additional avenue to undertake pilots and generate evidence on how to scale up the technology.

CONCLUSION AND POLICY IMPLICATIONS

Bangladesh is one of the most climate vulnerable countries in the world. The vulnerability is particularly severe in the coastal region of the country due to climate induced salinity intrusion (World Bank, 2022; GoB, 2021). This has threatened the livelihood of the farming community and led to higher rates of poverty and outmigration. One of the major policy responses has been developing STVR. Both the government of Bangladesh and its development partners have invested in developing these varieties for decades, but the adoption rate has hitherto been low. Using the Bangladesh Integrated Household Survey, conducted by the International Food Policy Research Institute (IFPRI), this study has attempted to examine the levels, determinants, and the impacts of these varieties on yields and farmers' income. A key feature of the BIHS is that the survey is representative at both national and division (administrative unit) levels and has collected detail information on farming practices and can thereby be used to carry out the analysis in a statistically robust way.

Results suggest that the STVR adoption rates remain indeed low at 26 percent. However, the impact analysis suggests that farmers who adopted the new strand of STVR had indeed benefitted in terms of both increasing yields and net incomes. Specifically, farmers who adopted STVR are estimated to have increased yield by 0.85 – 1.25 metric ton per hectare with an associated net income increase by US$100 - US$125 per hectare. On the other hand, if the non-adopters had adopted the STVR, their yield and net income would have gone up by as much as 2.4 tons and US$126 per hectare, respectively. Among other demographic factors, key constraints to adoption are found to be lack of access to agricultural extension, access to certified seed dealers, and agricultural implements. With these results, the paper argues that, despite profitability, the new generation of STVR is unlikely to be widely adopted unless the extension systems are strengthened, and farmers are incentivized through innovative institutional mechanisms. This, however, does not have to involve large subsidies. Important insights can be gathered by conducting studies following Theil's nudge theory - a strand of research that has gained wide popularity in the field of applied development economics.

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APPENDIX

Appendix-1: Salinity tolerant seed varieties in Bangladesh

Seed variety	Salinity level tolerance
BRRI dhan 47	• 12 – 14 dS m^{-1} at seedling stage up to 3 weeks • 6 dS m^{-1} at all growth stages • Potential to produce 4 t/ha yield • TVC – 768$/ha • Gross returns – 793$/ha • Gross margin – 25$/ha • BCR – 1.03 • Introduced in 2007
Binadhan – 8	• Soil salinity reaches up to 8 – 10 dS m^{-1} • 12 – 14 dS m^{-1} at seedling stage up to 3 weeks • Potential to produce 5 t/ha yield • TVC – 828$/ha • Gross returns – 935$/ha • Gross margin – 107$/ha • BCR – 1.13
Binadhan – 10	• Soil salinity reaches up to 8 – 10 dS m^{-1} • 12 – 14 dS m^{-1} at seedling stage up to 3 weeks • Potential to produce 5 t/ha yield • TVC – 828$/ha • Gross returns – 1107$/ha • Gross margin – 279$/ha • BCR – 1.34
BRRI dhan 28	• Soil salinity reaches up to 8 – 10 dS m^{-1} • Potential to produce 4 t/ha yield • TVC – 776$/ha • Gross returns – 881$/ha • Gross margin – 105$/ha • BCR – 1.09 • Introduced in 1994
Dyshary BR 23	• Salinity tolerance up to 8 dS m^{-1} • Yield potential of 4 t/ha • Introduced in 1988
BRRI dhan 40	• Salinity tolerance up to 8 dS m^{-1} • Yield potential of 5 t/ha • Introduced in 2003
BRRI dhan 41	• Salinity tolerance up to 8 dS m^{-1} • Yield potential of 5 t/ha • Introduced in 2003
BRRI dhan 53	• Salinity tolerance up to 8 dS m^{-1} • Yield potential of 4.5 t/ha • Introduced in 2010
BRRI dhan 54	• Salinity tolerance up to 8 dS m^{-1} • Yield potential of 5.5 t/ha • Introduced in 2010

Seed variety	**Salinity level tolerance**
BRRI dhan BR 55	• Medium salt tolerance of 8 – 10 dS/m up to 3 weeks • Drought tolerant • Yield potential of 7 t/ha • Introduced in 2011
BRRI dhan BR 61	• Salt tolerance of 12 – 14 dS/m up to 3 weeks at seedling stage and 8 dS/m at reproductive stage • Yield potential of 5 t/ha • Introduced in 2013

Source: Gregorio, G. B., Islam, M. R., Vergara, G. V., & Thirumeni, S. (2013). Recent advances in rice science to design salinity and other abiotic stress tolerant rice varieties.
Source: Singh, A.N., Sinha, D.D., Bari, M.A., Ismail, A. and Singh, U.S. 2012. Site Suitability Analysis for Dissemination of Salt-tolerant Rice Varieties in Southern Bangladesh. International Rice Research Institute Bangladesh Office, Dhaka. 161 p.
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Appendix 2: T-test quality of means before and after matching

Variable	Matched/ Unmatched	Treated	Control	% Bias	% Reduction in bias	t	p>t
Age	U	48.42	48.12	2.3	-421.6	0.61	0.54
	M	48.96	47.43	12.0		2.83	0.01
Household size	U	4.62	4.55	4.2	-44.8	1.14	0.254
	M	4.54	4.44	6.0		1.40	0.16
Asset index	U	0.45	0.44	13.3	38.9	3.43	0.01
	M	0.45	0.45	-8.1		-1.96	0.05
Education (Base: Illiterate)							
Primary and below	U	0.22	0.25	-8.2	10.7	-2.24	0.03
	M	0.22	0.25	-7.3		-1.61	0.11
Middle and secondary	U	0.28	0.30	-4.6	-199.9	-1.26	0.21
	M	0.29	0.24	13.8		3.13	0.02
Higher secondary and above	U	0.08	0.03	26.2	4.6	8.29	0.01
	M	0.04	0.10	-25.0		-5.01	0.01
Subsidy card (Yes = 1, No = 0)	U	0.19	0.28	-19.9	91.5	-5.33	0.01
	M	0.16	0.16	1.7		0.43	0.66
Tractor (Yes = 1, No = 0)	U	0.67	0.85	-41.1	50.9	-12.1	0.01
	M	0.71	0.79	-20.2		-4.36	0.01
Power tiller (Yes = 1, No = 0)	U	0.24	0.18	14.1	-71.0	3.99	0.01
	M	0.26	0.16	24.1		5.41	0.01
Land (Irrigated = 1, Rainfed = 0)	U	0.57	0.68	-22.4	75.1	-6.25	0.01
	M	0.56	0.59	-5.6		-1.19	0.23
Gender (Female = 1, Male = 0)	U	0.06	0.08	-7.8	-73.9	-2.10	0.04
	M	0.07	0.03	13.6		3.62	0.01
Pesticide dealer (Yes = 1, No = 0)	U	0.13	0.21	-20.6	93.3	-5.44	0.01
	M	0.13	0.14	-1.4		-0.33	0.74
Fertilizer dealer (Yes = 1, No = 0)	U	0.13	0.15	-7.0	-17.8	-1.91	0.06
	M	0.13	0.11	8.3		1.98	0.05
Seed dealer (Yes = 1, No = 0)	U	0.19	0.36	-39.4	78.6	-10.4	0.01
	M	0.19	0.16	8.4		2.14	0.03
Urea shop (Yes = 1, No = 0)	U	0.98	0.89	37.9	93.2	9.05	0.01
	M	0.98	0.99	-2.6		-1.10	0.27
Bank (Yes = 1, No = 0)	U	0.48	0.62	-28.3	51.3	-7.86	0.01
	M	0.51	0.44	13.8		3.00	0.01
Agriculture office Yes = 1, No = 0)	U	0.82	0.84	-4.5	-84.9	-1.26	0.21
	M	0.85	0.82	8.4		1.90	0.06
Mobile (Yes = 1, No = 0)	U	0.93	0.89	14.3	60.2	3.78	0.01
	M	0.92	0.94	-5.7		-1.45	0.15

Source: Authors' estimation

Appendix 3: CEM estimates - yield and income

Variables	Yield (tons/hectare)	Net income (US $/hectare)
Salinity tolerant seed adoption	3.613***	5,101.033***
(Yes = 1, No = 0)	(0.410)	(1,481.872)
Age	-0.074***	-32.674
	(0.020)	(90.551)
Household size	0.135	-1,440.871**
	(0.194)	(617.674)
Subsidy card (Yes = 1, No = 0)	-1.085	4,916.998*
	(0.688)	(2,853.118)
Asset index	2.218	7,266.011
	(3.091)	(10,915.952)
Education (Base: Illiterate)		
Primary and below	0.042	-13,738.593***
	(0.560)	(1,713.908)
Middle and secondary	0.662	-15,438.823***
	(0.631)	(1,897.009)
Tractor (Yes = 1, No = 0)	1.331***	5,832.157***
	(0.476)	(1,904.115)
Power tiller (Yes = 1, No = 0)	2.102**	20,900.466***
	(0.983)	(3,243.401)
Land (Irrigated = 1, Rainfed = 0)	6.872***	6,261.518***
	(0.526)	(2,234.452)
Bank (Yes = 1, No = 0)	-0.671	5,778.246***
	(0.518)	(1,815.832)
Agriculture office (Yes = 1, No = 0)	-4.186***	-1,565.596
	(0.673)	(5,926.746)
Mobile (Yes = 1, No = 0)	-2.029	5,921.006***
	(1.279)	(2,228.178)
Constant	15.041***	-4,988.827
	(2.202)	(8,270.707)
Observations	898	898
R-squared	0.435	0.242

Source: BIHS survey, 2015 – 16; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Appendix 4: ESR estimates - yield (tons/hectare)

Variables	Treatment = 1	Control = 0	Saline adoption
Log age	-1.800**	-0.538	11.656***
	(0.894)	(0.690)	(2.305)
Log household size	0.206	-2.030***	-1.264**
	(0.162)	(0.166)	(0.498)
Log age square	0.193*	0.072	-1.455***
	(0.117)	(0.091)	(0.306)
Log household size square	-0.058	0.704***	0.515***
	(0.056)	(0.058)	(0.171)
Gender (Female = 1, Male = 0)	-0.128***	0.076**	0.421***
	(0.041)	(0.032)	(0.103)
Subsidy card (Yes = 1, No = 0)	0.009	-0.077***	-0.318***
	(0.022)	(0.019)	(0.061)
Asset index	0.014	-0.924***	1.635***
	(0.165)	(0.132)	(0.404)
Education (Base: Illiterate)			
Primary and below	0.083***	-0.101***	0.132**
	(0.023)	(0.020)	(0.066)
Middle and secondary	-0.032	0.126***	-0.010
	(0.020)	(0.022)	(0.062)
Higher secondary and above	-0.241***	-0.199***	0.258**
	(0.041)	(0.050)	(0.120)
Tractor (Yes = 1, No = 0)	-0.026	-0.296***	0.532***
	(0.024)	(0.032)	(0.064)
Power tiller (Yes = 1, No = 0)	0.205***	-0.238***	-0.286***
	(0.025)	(0.026)	(0.066)
Land (Irrigated = 1, Rainfed = 0)	0.274***	0.358***	0.027
	(0.019)	(0.021)	(0.057)
Pesticide dealer (Yes = 1, No = 0)	-0.085**	0.224***	0.096
	(0.035)	(0.037)	(0.113)
Fertilizer dealer (Yes = 1, No = 0)	0.008	-0.117***	-0.777***
	(0.040)	(0.040)	(0.127)
Urea shop (Yes = 1, No = 0)	0.135*	-0.117***	-0.901***
	(0.071)	(0.032)	(0.129)
Bank (Yes = 1, No = 0)	-0.013	0.104***	0.376***
	(0.020)	(0.020)	(0.055)
Agriculture office (Yes = 1, No = 0)	-0.020	-0.021	0.305***
	(0.024)	(0.025)	(0.069)
Mobile (Yes = 1, No = 0)	0.067*	0.070**	0.193**
	(0.036)	(0.030)	(0.093)
Seed dealer (Yes = 1, No = 0)	-	-	0.910***
			(0.087)
Constant	6.792***	5.260***	-24.437***
	(1.734)	(1.277)	(4.298)
Observations	3,943	3,943	3,943

Source: BIHS survey, 2015 – 16; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Appendix 5: ESR estimates - net income (US $/hectare)

Variables	Treatment = 1	Control = 0	Saline adoption
Log age	1.110	-3.979	15.245
	(5.579)	(4.018)	(10.378)
Log age square	-0.139	0.489	-1.948
	(0.643)	(0.532)	(1.383)
Log household size	-6.633***	-0.691**	-0.925
	(1.987)	(0.341)	(1.997)
Log household size square	2.187***	0.207	0.339
	(0.683)	(0.172)	(0.774)
Gender (Female = 1, Male = 0)	0.777	-0.333**	0.168
	(0.684)	(0.140)	(0.250)
Subsidy card (Yes = 1, No = 0)	-0.024	-0.166	-0.280**
	(0.095)	(0.183)	(0.138)
Asset index	-0.402	0.790	1.020
	(2.107)	(0.614)	(2.568)
Education (Base: Illiterate)			
Primary and below	0.238	-0.320***	0.062
	(0.219)	(0.074)	(0.188)
Middle and secondary	0.166	-0.031	0.013
	(0.257)	(0.143)	(0.205)
Higher secondary and above	0.828	0.066	0.539
	(0.518)	(0.065)	(0.637)
Tractor (Yes = 1, No = 0)	-0.200	0.558**	0.578**
	(0.243)	(0.226)	(0.234)
Power tiller (Yes = 1, No = 0)	-0.113	0.448***	-0.116
	(0.195)	(0.093)	(0.514)
Land (Irrigated = 1, Rainfed = 0)	0.252***	0.099	0.249
	(0.030)	(0.090)	(0.261)
Pesticide dealer (Yes = 1, No = 0)	0.941***	0.075	0.106
	(0.209)	(0.178)	(0.366)
Fertilizer dealer (Yes = 1, No = 0)	-0.091	0.260	-0.709
	(0.325)	(0.306)	(0.845)
Urea shop (Yes = 1, No = 0)	0.703	-0.044	-1.043**
	(0.518)	(0.200)	(0.493)
Bank (Yes = 1, No = 0)	0.109	0.050	0.279***
	(0.205)	(0.031)	(0.102)
Agriculture office (Yes = 1, No = 0)	0.183	0.134	0.262
	(0.131)	(0.165)	(0.229)
Mobile (Yes = 1, No = 0)	-0.638	-0.237**	0.173
	(0.436)	(0.094)	(0.123)
Seed dealer (Yes = 1, No = 0)	-	-	0.913**
			(0.449)
Constant	11.708	17.316**	-30.559
	(12.683)	(7.746)	(18.747)
Observations	3,943	3,943	3,943

Source: BIHS survey, 2015 – 16; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

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