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Toward Rice Production Self-Sufficiency in Bangladesh: The Role of Plot Attributes, Farmer Characteristics, and Technology

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We examine the interdependence of high-yielding (HY) variety adoption and farm and farmer characteristics to achieve almost self-sufficiency in rice production in Bangladesh. We use data collected by the International Rice Research Institute (IRRI), Bangladesh, to estimate yield differentials, return differentials, and risk. We find that HY rice varieties contributed 61.34%, plot-specific attributes contributed 3.08%, and farmer-specific characteristics contributed 35.58% toward rice productivity. Additionally, adopting HY varieties resulted in a base return increase of about 154.03%. Plot-specific attributes had larger effects on the return model than on the differential yield model, while farmer-specific characteristics adversely impacted HY return gains.

Key words: farm characteristics, restricted/unrestricted yield gain

Introduction

Food security and food self-sufficiency are interrelated concepts, although food self-sufficiency is not required for food security. The Food and Agriculture Organization of the United Nations (1996) defines food security as a situation in which people have physical and economic access to sufficient, safe, and nutritious food to meet their dietary needs and food preferences for active and healthy lives all of the time. Food self-sufficiency is defined as a country producing a sufficient amount of food to feed its population. Producing food to achieve self-sufficiency may not be in the best interest of a country or its farmers, as production depends on input availability, the policy environment, and comparative advantage. However, food self-sufficiency has been the goal for staple food crops in many countries (Warr and Yusuf, 2014). These countries aim to be self-sufficient in staple food crop production (e.g., a goal of rice self-sufficiency in the Philippines, Indonesia, and China) by increasing agricultural productivity, increasing crop areas with high-yielding (HY) varieties (e.g., Bangladesh), output price support, imposing import tariffs, or providing fertilizer subsidies (e.g., Indonesia, China). The emergence of self-sufficiency in food production after the end of colonialism

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and reemergence after the wake of the international food crisis of 2007–2008 is particularly worth noting (Clapp, 2017).

The environmental impacts of agricultural production can be both positive and negative (Ball et al., 2004). Previous studies have highlighted several benefits of adopting modern technologies, including increased productivity (Chandio et al., 2022; Fuglie and Echeverria, 2024), economic gains (Walton et al., 2008), social advantages (Boyer et al., 2016; Fuglie and Echeverria, 2024), and environmental improvements (Huffman, Jin, and Xu, 2018; Chandio et al., 2022). For instance, agricultural mechanization re has significantly increased rice productivity in China (Chandio et al., 2022). Fuglie and Echeverria (2024) find that various agricultural technologies have led to higher crop productivity, reduced costs, increased profits, and provided cheaper products to the population. Walton et al. (2008) show that adopting precision soil sampling techniques is associated with increased productivity and income among cotton farmers. Boyer et al. (2016) find a positive link between adopting variable-rate nutrient management and participation in cost-sharing programs for social benefits. Busdieker-Jesse et al. (2016) find that genetically modified (GM) apple breeds improved profitability and reduced production costs for US apple producers. Similarly, adopting GM corn has been shown to increase productivity and reduce environmental degradation by improving soil moisture content (Huffman, Jin, and Xu, 2018). It is also worth noting that the Green Revolution and HY crop varieties have made many Asian and Latin American countries food secure or food self-sufficient in some crops (Sonnenfeld, 1992; Hazell, 2009; Dawson, Martin, and Sikor, 2016) despite HY varieties' long-term adverse environmental impacts (Tilman, 1998).

The agricultural sector is essential for achieving overall economic growth, development, and sustainability, thereby enhancing food security, producing employment opportunities, and alleviating poverty in many developing countries (Gollin, Parente, and Rogerson, 2002; Awokuse and Xie, 2015). Advanced agricultural technologies have been considered drivers of economic growth with the potential to alleviate poverty and reduce food insecurity (Barrett et al., 2004; Moreno and Sunding, 2005). Studies have long examined the introduction of improved varieties of seeds and agricultural inputs that increase yield in developing countries where farming by small landholders is predominant (Barrett et al., 2004; Moreno and Sunding, 2005; Kabunga, Dubois, and Qaim, 2014).

Nevertheless, there are limitations in the applicability (or application) and diffusion of these technologies. These limitations are related to the nature of economic and financial markets and the existence of information networks and information diffusion. Market-related attributes include credit constraints (Dercon and Krishnan, 1996; Fletschner, Guirkinger, and Boucher, 2010), information constraints (Kabunga, Dubois, and Qaim, 2014), social networks and social learning (Foster and Rosenzweig, 1995, 2010; Conley and Udry, 2010), and price risk (Liu, 2013; Ward and Singh, 2014). Besides, the extent to which these technologies could be adopted depends on farm and farmer characteristics. Farm-related attributes include farm size and plot biophysical conditions. Farmer-relevant variables include education and social network (Huffman, 2001; Skinner and Staiger, 2007), input utilization (Duflo, Kremer, and Robinson, 2008), risk preferences (Sunding and Zilberman, 2001; Dercon and Christiaensen, 2011), and seed trait preferences (Useche, Barham, and Foltz, 2009).

The process of establishing whether the adoption of new or improved technology is favorable compared to the old or traditional one proves challenging. The attributes that may deter the adoption of a new technology, let alone diffusion, need to be identified. A particular difficulty arises when the adoption of the new technology is more prominent due not to features of the new technology (e.g., seed traits, fertilizer, machinery) but rather to farmer attributes (e.g., education, training on new technologies) and cultivation practices (e.g., farmers being early adopters or selecting labor-saving technologies) (Huffman, 2001; Barrett et al., 2004; Useche, Barham, and Foltz, 2009). Studies have also reported that regional heterogeneity can affect technology adoption (Useche, Barham, and Foltz, 2009), which may lead to selection bias. We should expect farmers to apply that knowledge and technology to the fields they would most benefit from.

Our paper examines the interdependence of technology adoption decisions. Adoption based on technology, plot attributes, and farmer characteristics is important for smallholders where adoption conditions are heterogeneous. We use data from a Bangladeshi rice grower survey conducted by the International Rice Research Institute in 2015 that includes information on adopters and nonadopters of HY technology. We use differential yield and differential return function procedures (Barrett et al., 2004). We examine two rice-growing seasons and document changes in the yield and return differentials of farmers adopting HY technology for one season and using traditional rice varieties for the other season. This allows us to control for plot and farmer heterogeneity to a larger extent, allowing us to gain further insight into what drives these differentials. In addition, we quantify differential returns and cost functions.

Improved HY varieties of rice seeds, subsidized fertilizer, infrastructure developments, and improved management practices accompanied by government interventions liberalizing trade and agreements to lower tariffs for imported agricultural equipment ushered in the Green Revolution in Bangladesh in the mid-1980s, quite late compared to India or Mexico (Sonnenfeld, 1992; Hossain, Bose, and Mustafi, 2006). Despite an increase in population and a decrease in arable land, adopting these technologies since the Green Revolution has helped accelerate the production of food grains in the country. As a result, Bangladesh has almost achieved self-sufficiency in rice production (Food and Agriculture Organization of the United Nations, 2015), making the country an ideal subject for researching the role of improved farming technologies in achieving food self-sufficiency. Further, considering that Bangladesh relies on agriculture, particularly rice production, to feed its population, food insecurity would increase if there were insufficient domestic production (Timsina et al., 2018). Bangladesh's population of 168 million in 2022, which is expected to increase to 186 million by 2030, makes it crucial to identify both the factors affecting rice production technologies and their role in food sufficiency in Bangladesh.

The empirical results indicate that the application of HY technology generated an estimated 61.34% increase in rice yield. An estimated 35.58% was attributed to individual rice grower characteristics adding to the literature that highlights the interrelation of farmer characteristics and technology adoption decisions. Last, an estimated yield increase of 3.08% was attributed to plot attributes. Similarly, our analysis of differential return function estimates showed that the return increase was caused by HY variety adoption (78.68%), plot attributes (31.63%), and farmer characteristics (−10.31%). By quantifying the role of HY varieties, plot attributes, and farmer characteristics, we can better understand each component's role in achieving rice self-sufficiency in Bangladesh.

We organize the remainder of the paper as follows. We describe the rice-growing system in Bangladesh and introduce the HY technology in section II. In section III, we present the empirical framework and the econometric specification. We describe the data used in the study in section IV. The later sections report our findings, main observations, and concluding remarks.

Country Background

Bangladesh is a deltaic country in South Asia with a land area of about 147,550 square kilometers. It is one of the most populous countries in the world, ranking 13th in population density, with approximately 1,077 people per square kilometer (Timsina et al., 2018; Mottaleb, Rahut, and Erenstein, 2019). Varieties of rice—a staple food item in Bangladesh—are planted in three seasons: Aman season varieties are cultivated during the "wet" season (mid-July to mid-November), Boro season varieties are cultivated during the "dry" season (mid-November to mid-March), and Aus varieties are cultivated in the spring (mid-March to mid-July) (Food and Agriculture Organization of the United Nations, 2019). Aman season rice varieties consist of mainly traditional rice varieties that are rainfed and require less fertilizer; these varieties are susceptible to drought as well as flood (Asaduzzaman et al., 2010). High-yielding Boro season rice varieties rely on improved management practices, including transplanting in well-spaced rows, heavy use of chemical fertilizers, and groundwater irrigation (Ruane et al., 2013; Timsina et al., 2018; Mottaleb, Rahut, and Erenstein, 2019). Aus season rice varieties have been sparsely cultivated in the last few decades for various reasons such as high cost of production and higher incidence of weeds and pests associated with those varieties (Asaduzzaman et al., 2010). According to data from the USDA Foreign Agricultural Service (2025), Aman season rice varieties accounted for 39% of total rice production in the country, Aus season varieties contributed 8% and Boro season varieties contributed 54% between 2018 and 2020.

Following trade liberalization on importing small-scale irrigation equipment (Mottaleb et al., 2017; Mottaleb, Rahut, and Erenstein, 2019) and intensive use of chemical fertilizer, HY/modern rice varieties covered about 85% of total rice area in 2016–2017, up from only about 15% in 1981–1982 (Bangladesh Rice Research Institute, 2018; Mottaleb, Rahut, and Erenstein, 2019). With the increase in population, per capita cultivable area has been declining since the 1960s (Mottaleb, Rahut, and Erenstein, 2019). In 2013, per capita arable land was about 0.005 hectares, down from 0.17 hectares in 1961 (World Bank, 2017; Mottaleb, Rahut, and Erenstein, 2019). In 1982, the net cultivable area was about 9.83 million hectares. It had declined dramatically to 8.7 million hectares by 1992–1993 and 7.77 million hectares by 2008–2009 (Alam and Islam, 2013).

Changes in government policies (which had favored privatization in the procurement and distribution of small-scale irrigation equipment and chemical fertilizers), trade liberalization, and reduction in tariffs for imported agricultural equipment were also factors that contributed to HY adoption (Mottaleb et al., 2017; Mottaleb, Rahut, and Erenstein, 2019). Private investment in small-scale irrigation equipment was considered a dominant factor in facilitating the diffusion of HY varieties (Asaduzzaman et al., 2010; Mottaleb et al., 2017; Mottaleb, Rahut, and Erenstein, 2019). Beginning in 1986, the government removed the ban on private sector imports of agricultural equipment. As a result, the cost of tube wells was reduced substantially, and a market for irrigation services was developed (Hossain et al., 2003). As a result, farmers invested substantially in shallow tube wells and power pumps, contributing to rapidly expanding irrigation facilities. The diffusion of HY Boro rice is strongly related to the expansion of groundwater irrigation (Asaduzzaman et al., 2010; Mottaleb, Rahut, and Erenstein, 2019).

The upward trends in rice cultivation area, yield, and production volume in Bangladesh have been noticeable since adopting HY varieties (Ricepedia, 2019). In terms of productivity, the average rice yield increased from 2.15 tons/ha in 1984 to 4.42 tons/ha by 2014, a 2.4% annual growth rate (Alam and Islam, 2013; Ricepedia, 2019). Bangladesh almost achieved self-sufficiency in 2016, but extreme weather events in 2017 (including heavy monsoons that led to flooding in the major rice-growing areas of Dhaka and Rajshahi) resulted in lower total (US Department of Agriculture, 2017, 2018) production; in 2018, the country produced a surplus of rice.[1] Yields of traditional varieties (TV) have also increased, from 1.52 tons/ha in 1965 to 2.14 tons/ha by 2009, an annual growth rate of 0.9% (Hossain et al., 2003; Alam and Islam, 2013). Major factors leading to an increase in the yield of TVs include the increase in the use of chemical fertilizers and a reduction in the share of land cultivated with Aus season rice varieties (Hossain et al., 2003).

Method

Several studies have examined the adoption of agricultural innovation while considering the diverse characteristics of farmers, farms, and farming regions in an empirical setting. Abay et al. (2016) explore the adoption of fertilizer, seed, and extension services while considering farm household-level unobserved heterogeneity (e.g., risk-taking and technology preferences). Tran-Nam

[1] In 2018, total rice production in Bangladesh exceeded domestic needs by 7 million tons. The USDA forecast 11.62 million hectares of rice harvested area and 3.59 million metric tons produced in Bangladesh for the marketing year 2021/2022, slightly up from the previous year. The government of Bangladesh continues to import rice to make it affordable. It was estimated that Bangladesh would import 1.5 million metric tons of rice in marketing year 2021/2022 (US Department of Agriculture, 2022).

and Tiet (2022) determine the sociodemographic determinants of organic farming adoption while accounting for individual heterogeneity in environmental belief. Varshney et al. (2022) examine the adoption of hybrid mustard in India while considering heterogeneity across different castes of farm producers. Barnes et al. (2019) consider regional heterogeneity while examining the internal and external determinants of adopting precision agricultural technologies and nitrogen technologies in EU farming systems. Similarly, Shahzad and Abdulai (2021) examine the adoption of climate-smart agricultural technology in Pakistan while empirically accounting for unobserved household characteristics. Further, several past studies have summarized agricultural technology adoption literature and discussed heterogeneity, mainly in the context of developing countries (Feder, Just, and Zilberman, 1985; Ruzzante, Labarta, and Bilton, 2021; Oyetunde-Usman, 2022).

In this study, the empirical model estimates a differential yield function and a differential return function controlling for farmer characteristics and plot attributes (Barrett et al., 2004). We observe the same individuals cultivating the same plots in two consecutive seasons within a year. This allows us to capture the true productivity gains and risks of HY technology by identifying the effects of technology adoption and the marginal productivity of land and labor inputs. Depending on whether one chooses a production or profit/cost approach, there is a need to address the endogeneity problem.[2]

Production systems are affected by seasonality and are susceptible to stress factors (e.g., extreme weather events, pests, diseases) during the production period. Grain producers likely respond to seasonal conditions by adjusting the input mix under some production decision rigidity or by adjusting the output mix (Tozer and Villano, 2013). Tsiboe et al. (2017) argue that improving rice varieties, making them more disease resistant, has the potential to increase both rice production and overall consumer surplus. The limited resources used in rice cultivation in Bangladesh may deter farmers from reallocating resources, given that the seasons for cultivating rice varieties succeed one another. Moreover, due to the country's dependence on agriculture for food-security concerns and high population density, fields are seldom left uncultivated. However, that does not necessarily mean those producers can easily switch between crop production or alter their production practices.

To proceed, for each of the technologies (y) examined, HY and traditional varieties, we define the respective yield functions:

$$\text{HY: } y_f = y_f(\boldsymbol{x}, \boldsymbol{z}) \tag{1}$$

$$\text{TV: } y_g = y_g(\boldsymbol{x}, \boldsymbol{z}) \tag{2}$$

Each technology is characterized by a vector of production inputs ($\boldsymbol{x}$) controlled by the farmer and a vector of exogenous characteristics related to farm, farmer, and environmental conditions ($\boldsymbol{z}$). For our study, vector $\boldsymbol{x}$ contains information on land use, labor usage and cost, fertilizer application and cost, pesticide cost, herbicide cost, and irrigation cost. Vector $\boldsymbol{z}$ contains information on environmental conditions, plot attributes, and farmer characteristics. Environmental conditions are proxied by days of water shortage; plot attributes include average plot size and soil quality; farmer characteristics include farmer age, experience with HY varieties, gender, and education.[3] Rice cultivation in Bangladesh is prone to production risk. To account for the production risk, we allow inputs to have either positive or negative marginal effects on production. The two technologies

[2] Estimating a production or yield function is the primal approach, whereas estimating profit or cost function is the dual approach. In the dual approach, the selection of inputs and respective quantities are endogenous. There are advantages and disadvantages in using either of these approaches; based on the scenario we examined, we believe that the best approach is to employ a primal model. The dual is not efficient because it fails to utilize all the available information (Mundlak, 1996).

[3] Vector $\boldsymbol{z}$ could also include unobservable farmer characteristics, such as farmer health, energy level, work ethic, farming aptitude (Barrett et al., 2004).

can be represented by the general functional forms, following Just and Pope's (1978) formulation:

$$\text{HY}: y_f = f(\boldsymbol{x}, z) + h_f(\boldsymbol{x}, z)^{\frac{1}{2}} \xi_f\,; \tag{3}$$

$$\text{TV}: y_g = g(\boldsymbol{x}, z) + h_g(\boldsymbol{x}, z)^{\frac{1}{2}} \xi_g\,; \tag{4}$$

where ξ is a shock with mean zero and variance σ_i^2 $(i = f, g)$ that is independent across the cross-sectional observations. The conditional expectation functions for y_f and y_g are $f(\boldsymbol{x}, z)$ and $g(\boldsymbol{x}, z)$, respectively.

Following Barrett et al. (2004), we employ a first-order approximation with interaction effects to the true conditional expectation function for each technology:[4]

$$\begin{aligned} E\left[y_f\right] = {} & \alpha_{f0} + \sum_{i=1}^{r} \alpha_{fi} \boldsymbol{x}_{fi} + \sum_{i=1}^{r} \sum_{j=1 \neq i}^{r} \beta_{fij} \boldsymbol{x}_{fi} \boldsymbol{x}_{fj} + \sum_{i=1}^{t} \gamma_{fi} \boldsymbol{z}_{fi} \\ & + \sum_{i=1}^{t} \sum_{j=1 \neq i}^{t} \eta_{fi} \boldsymbol{z}_{fi} \boldsymbol{z}_{fj} + \sum_{i=1}^{r} \sum_{j=1}^{t} \tau_{fij} \boldsymbol{x}_{fi} \boldsymbol{z}_{fj}\,; \end{aligned} \tag{5}$$

$$\begin{aligned} E\left[y_f\right] = {} & \alpha_{f0} + \sum_{i=1}^{r} \alpha_{fi} \boldsymbol{x}_{fi} + \sum_{i=1}^{r} \sum_{j=1 \neq i}^{r} \beta_{fij} \boldsymbol{x}_{fi} \boldsymbol{x}_{fj} + \sum_{i=1}^{t} \gamma_{fi} \boldsymbol{z}_{fi} \\ & + \sum_{i=1}^{t} \sum_{j=1 \neq i}^{t} \eta_{fi} \boldsymbol{z}_{fi} \boldsymbol{z}_{fj} + \sum_{i=1}^{r} \sum_{j=1}^{t} \tau_{fij} \boldsymbol{x}_{fi} \boldsymbol{z}_{fj}\,; \end{aligned} \tag{6}$$

To estimate the effect of the technology adoption on yield, we subtract equation (6) from equation (5):

$$\begin{aligned} dy = {} & \alpha_0 + \sum_{i=1}^{r} \alpha_i dx_i + \sum_{i=1}^{r} \sum_{j=1 \neq i}^{r} \beta_{ij} dx_i dx_j + \sum_{i=1}^{t} \gamma_i dz_i \\ & + \sum_{i=1}^{t} \sum_{j=1 \neq i}^{t} \eta_{ij} dz_i dz_j + \sum_{i=1}^{r} \sum_{j=1}^{t} \tau_{ij} dx_i dz_j + d\varepsilon, \end{aligned} \tag{7}$$

where $dy = E\left[y_f\right] - E\left[y_g\right]$ is the difference in expected output or return, $d\boldsymbol{x} = \boldsymbol{x}_f - \boldsymbol{x}_g$ reflects the difference in input application rates or input costs on plots using the two different technologies, $dz = z_f - z_g$ reflects exogenous differences in the plots (e.g., soil type), and $d\varepsilon = \varepsilon_f - \varepsilon_g$ is a mean 0, independent error term. The parameters α_i, β_{ij}, γ_i, η_{ij}, and τ_{ij} directly estimate the marginal productivity differences between the two technologies.

By differencing the characteristics of vectors $\boldsymbol{x}$ and z, we can remove potential bias from omitted but similar unobserved characteristics. Hence, when estimating equation (7) (i.e., the difference in expected output or return), we obtain consistent and unbiased estimates of the marginal productivity differences (gains) attributable to HY technology. These productivity gains can be decomposed into gains from (i) switching to a better technology, (ii) plot quality, or (iii) farmer characteristics. The gains from the marginal productivity of inputs are calculated as the product of the slope parameter estimates from equation (7) and the sample mean of the vector $\boldsymbol{x}$ variables. The same approach is used to calculate plot-attribute specific gains (vector z variables).

Unconditional productivity and gross return gains from the new technology are equal to the corrected base productivity change estimate plus the estimated direct effects of experience with the

[4] Equations (5) and (6) can be converted into a standard regression model by adding a zero mean of normally distributed *i.i.d.* error term.

new technology multiplied by the sample mean experience level. Any farmer-specific gains are the residual production or portion of the yield differential not attributed to input, plot, and unconditional productivity gains.

Return Risk Estimation

As mentioned previously, managing production risks related to production practices and stress factors affecting production is important to farmers. Risk in this framework is the variation from expected output across farms. Following Barrett et al. (2004), we define the differential production risk function to be the difference in output variance attributable to changing technologies as

$$S^2 = V\left[y_f\right] - V\left[y_g\right] = E\left[\varepsilon_f^2 - \varepsilon_g^2\right] = h(\boldsymbol{x},\boldsymbol{z}), \tag{8}$$

which can be estimated by differencing the squared residuals from the two technology-specific production and gross return functions. The variance will be regressed on the $\boldsymbol{x}$ and $\boldsymbol{z}$ vectors. Notice that the variance is a function of the $\boldsymbol{x}$ and $\boldsymbol{z}$ vectors; that is, the observable farmer-specific (e.g., age, education) or plot-invariant effects (e.g., days of water shortage). Following the method on production differentials, we take the first-order approximation with interaction effects to the true conditional variance function (h function). The differential production risk function can be estimated as

$$s^2 = \theta_0 + \sum_{i=1}^{r}\theta_i \boldsymbol{x}_i + \sum_{i=1}^{r}\sum_{j=1\neq i}^{r}\lambda_{ij}\boldsymbol{x}_i\boldsymbol{x}_j + \sum_{i=1}^{t}\varphi_i \boldsymbol{z}_i + \sum_{i=1}^{t}\sum_{j=1\neq i}^{t}\delta_{ij}\boldsymbol{z}_i\boldsymbol{z}_j + \sum_{i=1}^{r}\sum_{j=1}^{t}\omega_{ij}\boldsymbol{x}_i\boldsymbol{z}_j + \psi, \tag{9}$$

where ψ is a mean zero *i.i.d.* error term on the differential conditional variance regression, the parameters will be interpreted similarly with respect to production risk. The slope coefficients estimate the marginal risk effects of the new technology as physical input or cost input application rates vary. The net mean changes in risk due to farm- and farmer-specific (excluding plot-variant) characteristics and the true unconditional change in production and return risks are captured by θ_0.

Given the limitation of cross-sectional data, it is crucial to determine the effects associated with technology separately from those due to the unobserved farm or plot attributes; otherwise, the estimated effects of new technology will be overestimated (Barrett et al., 2004). The method used, including the estimation of the production function instead of the profit function, as indicated by (Barrett et al., 2004, p. 881), "permits proper attribution of observed gains between the technology and underlying farmer characteristics and plot attributes associated with the adoption of the new technology." Thus, our approach appropriately assigns the observed yield due to technology accounting for those due to producer characteristics or plot attributes.

Chen and Yen (2006, p. 764) argue that the Barrett et al. (2004) approach with "additional cross-product terms causes specification errors and potentially biased parameter estimates." This is because the parameter in equation (7), without correction, "incorporates output gains associated with adopters' observable and unobservable attributes that may not be replicable in the broader population of nonadopters" (Barrett et al., 2004, p. 881). We considered the corrections for equal slope coefficient and cross-product terms, as suggested by (Chen and Yen, 2006). Chen and Yen (2006) suggest three ways to overcome the problems: differencing, fixed effects, and random effects. We use the first-differenced model that assume equal slope coefficients, treating each interaction term as a regressor and taking the difference of corresponding interaction terms instead of using the product of differences. Base productivity gains found from the resulting intercept term provided consistent estimates, which are free from the bias caused by farm- or farmer-specific unobserved heterogeneity (Chen and Yen, 2006). We expect higher productivity, more labor hours, more years of experience, richer soils, high fertilizer application, and fewer water shortages to be positively correlated with higher yields and returns.

Table 1. Farm and Farmer Characteristics (N = 659)

Panel A. Farmer and Farm Characteristics	Mean	Min.	Max.
Farmer Characteristics			
Mean age of farmer (years)	46.86 (12.45)	17	86
Percentage male operators	88.01		
Percentage of farmers trained about HY varieties	81.18		
Percentage of farmers with no education	34.29		
Percentage of farmers with high school education or better	22.75		
Farm Characteristics			
Mean total rice area (acre)	0.98 (0.57)	0.16	4.47
Percentage of rice land in HY varieties	51.79 (20.47)		
Percentage of farmers own tractors and tube wells	43.85		

	High-Yielding Varieties			Traditional Varieties		
Panel B. Rice Cultivation Methods	**Mean**	**Min.**	**Max.**	**Mean**	**Min.**	**Max.**
Mean area of plot (acre)	0.49 (41.55)	0.04	2.70	0.48 (35.82)	0.05	2.97
Mean years of experience with method	8.51 (3.69)	2	22	28.40 (12.22)	2	76
Mean days of water shortage in field	1.90 (0.30)	1	2	1.74 (0.43)	1	2
Percentage of fields on rich soils	70.23			70.23		
Percentage using chemical fertilizer	100			100		
Mean yield (kg/acre)	2,155 (432)	420	3,800	931 (436)	222	2,960

	High-Yielding Varieties			Traditional Varieties		
Panel C. Returns and Prices	**Mean**	**Min.**	**Max.**	**Mean**	**Min.**	**Max.**
Return from HY variety rice (TK/acre)	37,040.23 (10,754)	6,062	108,771	31,909 (21,184)	4,380	184,800
Price of rice (TK/kg)	17.16 (3.41)	10	39	34.34 (13.58)	10	73

Notes: Values in parentheses are standard deviations. Returns and prices are measured in Bangladeshi taka. (US$1 = Tk 116.42 as of August 4, 2024.)

Data

We use data collected by the International Rice Research Institute (IRRI) office in Bangladesh. IRRI conducted an Area-Based Farm Household Survey in Bangladesh in 2015 for rice cultivation in 2014. IRRI randomly selected the samples and collected information on rice production from 3,000 farmers. A pretested survey questionnaire was used, and data collection was conducted by trained enumerators covering 18 districts of Bangladesh.

Our dataset comprises 659 observations based on farmers who cultivated both HY and traditional rice varieties in 2014. Initially, there were 740 observations; after data cleaning to remove outliers and incorrect/inconsistent data entries, we used 659 observations in the analysis. Due to a relatively small dataset and to maintain consistency with Barrett et al. (2004), we did not consider regional (district) variations. We isolate responses from farmers (household heads) who cultivated both HY and traditional rice varieties during the Boro and Aman seasons, respectively. As mentioned earlier, HY varieties are mostly cultivated during the Boro season, while TVs are mostly cultivated during the Aman season. The dataset reports information on cultivation details, irrigation practices, ownership of farm machinery, training, and plot and farmer characteristics. Table 1 presents the summary statistics of our sample.

Panel A of Table 1 describes key farmer and farm characteristics from the sample. The average age of farmers was about 47 years, with a minimum of 17 years and a maximum of 86 years. Farming is a way of life in Bangladesh, and operators start farming at an early age. About 88% of the farm operators were male, and 81% of farm operators received training in HY rice cultivation methods through local extension agents. About 34% of the farmers had no formal education, while 22.75% had received at least a high school education. The average education level of the farm operators was about 5 years; that is, up to the level of primary education in Bangladesh. Moser and Barrett (2003) find that adopters of new technology are relatively well-educated, more involved in farmer organizations, and own more rice land compared to nonadopters. These characteristics for adopters were also true for Bangladeshi farmers. Bangladeshi rice farmers cultivated small plots (mostly marginal < 1 acre) with an average cropped area of 0.98 acres (2.47 acres = 1 hectare). About 52% of the total area under rice production was done using HY varieties. About 44% of the farmers own a tractor/power tiller and/or diesel or electricity-operated tube wells.

Panel B of Table 1 presents information on the two cultivation practices examined in this study, namely HY and traditional rice varieties. On average, the farm size used for rice cultivation was about 0.49 acres in each season (two seasons, so the effective area was 0.49*2 = 0.98 acres). On average, 0.49 acres were cultivated with HY varieties in the Boro season, with a minimum of 0.04 and a maximum of 2.70 acres. For TVs, on average, 0.48 acres were cultivated in the Aman season, with a minimum of 0.05 and a maximum of 2.97 acres. This shows that an average Bangladeshi farmer owns a small land plot and allocates the maximum share of this land for rice production. More importantly, Bangladeshi farmers use the same land or plot to cultivate different crops in different seasons.

The surveyed farmers had, on average, about 9 years of experience with HY technology, with a minimum of 2 years and a maximum of 22 years. For TVs, on average, farmers had about 28 years of experience cultivating TVs, with a minimum of 2 years and a maximum of 76 years. Taking into consideration the age profile of rice growers in the sample, we expect to see a difference regarding the years of experience in the respective technologies. As mentioned earlier, HY varieties were introduced in the mid-1980s in Bangladesh, and based on our sample, we see that the adoption of HY varieties is a continuous and ongoing process. Despite the introduction of HY varieties, the average areas under HY and traditional rice cultivation are found to be almost the same. Both varieties are predominately cultivated in Bangladesh based on the season.

Bangladesh is rich in alluvial soil as a result of major rivers—such as the Ganges and Brahmaputra—flowing through the country.[5] This alluvial land is highly fertile and suitable for rice cultivation. The surveyed farmers reported that 70% of the land allocated to rice production under both methods was of high quality. Nevertheless, all surveyed farmers applied chemical fertilizer in the production process. No use of manure was reported for the cultivation practices. We observe the main differences regarding rice yield under the two technologies. The average yield was about 2,155 kg/acre for HY varieties and about 931 kg/acre for TVs. The maximum yield was 3,800 kg/acre for HY varieties and 2,960 kg/acre for TVs.

[5] These rivers are known as Padma and Jamuna, respectively, in Bangladesh.

Table 2. Productivity of Land and Labor

	High-Yielding Varieties		Traditional Varieties		Mean Difference (%)	
	Yield (kg/acre)	Return (TK/acre)	Yield (kg/acre)	Return (TK/acre)	Yield	Return
Output/return	2,154	37,040	931	31,909	131	16
	(432)	(10,754)	(436)	(21,184)		
Labor productivity	146	11.22	128	17.9	14	−37
Nonharvest labor	14.75	3,299	7.24	1,782	103	85
	(15.06)	(2,059)	(10.18)	(1,432)		

Notes: Values in parentheses are standard deviations. Returns are measured in Bangladeshi taka. (US$1 = Tk 116.42 as of August 4, 2024.)

Panel C of Table 1 represents returns and prices of rice yields in Bangladesh for both technologies and seasons. The average return on HY rice production was about Tk 37,040/acre,[6] with a maximum of Tk 108,771/acre and a minimum of Tk 6,062/acre. On average, the return on TV rice production was about Tk 31,909/acre, with a maximum of Tk 184,800/acre and a minimum of Tk 4,380/acre. The average returns were almost similar because of average prices: about Tk 17/kg for HY rice and about Tk 34/kg for TV rice. This price difference is attributed to rice quality; that is, HY varieties are mostly coarse grain and are used for home consumption by farmers year-round. TVs are mostly aromatic with fine grains; as a result, farmers earn a higher price compared to the price of HY varieties. Moreover, Bangladeshi farmers sell rice just after harvesting, except for a few large farmers who may have storage facilities and can sell rice later in the season. This explains why prices range from Tk 10/kg to over Tk 70/kg within a year. There is no operating futures market in the country, but farmers can get higher prices if they sell outside of the immediate harvesting time. It is worth noting that the international rice markets are integrated with efficient pricing mechanisms (Chen and Saghaian, 2016).

Table 2 reports unconditional land and labor productivity. Output, labor productivity, and nonharvest labor are measured in terms of both physical and monetary terms. Labor productivity is calculated by dividing the outputs and returns by nonharvest labor days and the cost of nonharvest labor. Nonharvest labor is measured in both man-days and taka per acre. Results show that HY plots have a 231% higher yield than TV plots but only 16% higher returns. A t-test confirms that there are significant differences in yield and returns between these two varieties (t-value: 49.80 with $p = 0.000$, and t-value 5.60 with $p = 0.000$, respectively). Based on standard deviations, physical output varies more under TVs than under HY varieties, and returns vary more under HY varieties than under TVs. This increased yield risk under TV practices may be attributed to a lack of timely availability of fertilizer, labor to transplant seedlings, and a shortage of groundwater. Increased return risk may be attributed to farmers' needs and desires (specifically, whether they sell immediately after harvesting or store rice for future sales). The use of nonharvest labor days for HY varieties is almost double that of the nonharvest labor days for TVs. In Bangladesh, farmers use tractors to cultivate land for seedbed preparation, land preparation, harvesting, and threshing. Only a limited number of laborers are employed in transplanting, fertilizer application, and insecticide application, which are mostly family labor tasks.

Figure 1 illustrates the median and span of labor use ratio in physical terms. We find that in the early adoption stage (experience), labor demand increases for HY varieties compared to TVs; then, the ratio of (HY variety/TV) labor utilization decreases and remains slightly above 1 for the remaining periods. With increased experience with HY varieties, after about 4 years, the ratio of HY varieties and TV early season labor utilization becomes parallel to the horizontal axis. This could be attributed to the farmers' learning by doing. When adopting a new technology, farmers tend to utilize more labor inputs. As time passes, they tend to adopt similar management practices for both technologies. As a result, after a few years of experience, labor input utilization becomes almost similar.

[6] Prices are measured in Bangladeshi taka. US$1 = Tk 116.42 as of August 4, 2024. See: https://www.xe.com/currencyconverter/convert/?Amount=1&From=USD&To=BDT

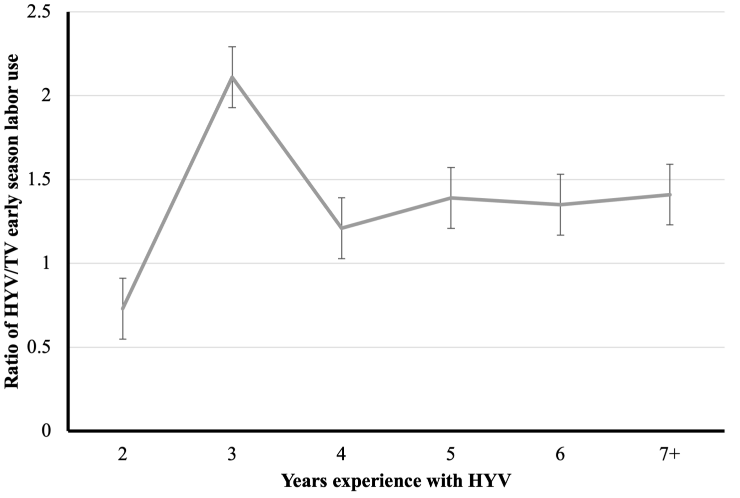

Figure 1. Median and Span of Labor Use Ratio

Notes: HYV = high-yielding varieties of rice, TV = traditional varieties of rice.

Table 3. Estimated Difference in Mean Rice Yields Under High-Yielding Varieties (*N* = 659)

Variables	Unrestricted Random Effects Model 1	Differential Yield Model 2	Restricted Random Effects Model 3
Base productivity change	2,235***	1,230***	1,230.52***
	(132.54)	(69.33)	(24.33)
Marginal yield changes land (acre)	48.18	98.11	98.11
	(103.67)	(79.34)	
nonharvest labor (days/acre)	−2.04	−3.48	−3.48
	(2.95)	(4.40)	
Experience (years)	−2.92	0.94	0.94
	(9.26)	(2.47)	
Rich soils (dummy)	54.39	53.89	53.89
	(37.40)	(55.27)	
Fertilizer application (kg/acre)	0.06	0.03	0.03
	(0.36)	(0.39)	
Days of water shortage	−40.53	−123.62***	−123.62***
	(49.15)	(47.36)	
Land × experience	−12.05	0.95	0.95
	(13.29)	(3.63)	
Labor × experience	0.26	−0.12	−0.12
	(0.37)	(0.19)	
R^2	0.02	0.02	

Notes: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses are standard errors. Columns 1, 2, and 3 show the regression results for mean rice yield (kg/acre) associated with the unrestricted random effects model, the differential yield model, and the restricted random effects model, respectively. The unrestricted random effects model fails to control for farm- and farmer-specific characteristics. Therefore, these estimates are biased and inconsistent. The differential yield model estimates Model 5 and considers the difference in yield between high-yielding (HY) and traditional varieties (TV). The restricted random effects model provides a consistent estimate of base productivity change and other parameters.

Table 4. Estimated Difference in Variance of Rice Yields Under High-Yielding Varieties (N = 659)

Variables	Unrestricted Random Effects Model 1	Differential Yield Model 2	Restricted Random Effects Model 3
Base productivity change	89.53	−42.7	−42.72
	(156.11)	(118.47)	−34.53
Marginal yield changes land (acre)	−269.91**	240.14***	240.14***
	(105.54)	(91.99)	
nonharvest labor (days/acre)	0.93	0.87	0.87
	(5.05)	(6.61)	
Experience (years)	−8.69	4.85	4.85
	(13.51)	(3.67)	
Rich soils (dummy)	32.69	163.55**	163.55**
	(40.60)	(86.46)	
Fertilizer application (kg/acre)	0.09	0.69	0.69
	(0.46)	(0.46)	
Days of water shortage	100.16**	19.06	19.06
	(49.10)	(65.97)	
Land × experience	36.61***	5.29	5.29
	(13.86)	(4.75)	
Labor × experience	0.13	0.01	0.01
	(0.68)	(0.27)	
R^2	0.02	0.02	–

Notes: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses are standard errors. Columns 1, 2, and 3 show the regression results for the variance of rice yield associated with the unrestricted random effects model, the differential yield model, and the restricted random effects model, respectively. The unrestricted random effects model fails to control for farm- and farmer-specific characteristics. Therefore, these estimates are biased and inconsistent. The differential yield model estimates Model 5 and considers the difference in yield between high-yielding varieties and traditional varieties . The restricted random effects model provides a consistent estimate of base productivity change and other parameters.

Results and Discussions

Tables 3–6 report the regression results for rice yield and returns. In these tables, column 1 shows the coefficient estimates of the unrestricted random effects regression model, which fails to control for farm- and farmer-specific effects. Therefore, these estimates are biased and inconsistent. Column 2 in these tables displays the differential yield function estimates from equation (7). The marginal yield effect estimates are consistent, but the base productivity gain is not consistent. That is, the parameter estimates of each explanatory variable (e.g., land, labor, experience) are consistent, but the constant (base productivity change) is not consistent. Column 3 in each table reports the corrected base productivity change estimate from the restricted random effects. For the restricted random effects, the slopes are restricted to equal the estimates generated by the preceding differential yield function (column 2).

Tables 3 and 4 show the estimated difference in mean and variance of yields of HY varieties. Results indicate that base productivity gains are almost twice as high under the unrestricted model than in the restricted random effects model. Note that the restricted model is estimated with proper controls for observable accounting unobservable characteristics. The differential yield model's base productivity gains are also almost similar, differing from Barrett et al. (2004), who find the estimate to be 84% higher. This could imply that farmers use similar inputs for both varieties. Once we difference away farm- and

Table 5. Estimated Difference in Mean Returns Under High-Yielding Varieties (N = 659)

Variables	Unrestricted Random Effects Model 1	Differential Yield Model 2	Restricted Random Effects Model 3
Base productivity change	44,704*** (2,693)	7,904.6** (3,118)	7,903.5*** (908)
Marginal yield changes land (Tk/acre)	−1,269.86 (1,106)	2,577 (1,710)	2,577
Nonharvest labor cost (Tk/acre)	−0.08 (0.21)	−0.20 (0.41)	−0.20
Experience (years)	−263.25** (103.40)	67.85 (84.32)	67.85
Rich soils (dummy)	275.37 (1,046)	2,319.8 (2,170)	2,319.8
Fertilizer application cost (Tk/acre)	0.19 (0.18)	−0.38 (0.34)	−0.38
Days of water shortage	−2,537.81** (1,179)	−3,573.9** (1,676.7)	−3,573.9**
Irrigation cost (Tk/acre)	−0.02 (0.14)	−0.13 (0.30)	−0.13
Insecticide/pesticide cost (Tk/acre)	−0.89 (0.88)	−1.83 (1.75)	−1.83
R^2	0.02	0.02	

Notes: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses are standard errors. Columns 1, 2, and 3 show the regression results for average returns (Tk/acre) associated with the unrestricted random effects model, the differential yield model, and the restricted random effects model, respectively. The unrestricted random effects model fails to control for farm- and farmer-specific characteristics. Therefore, these estimates are biased and inconsistent. The differential yield model estimates Model 5 and considers the difference in yield between high-yielding (HY) and traditional varieties (TV). The restricted random effects model provides a consistent estimate of base productivity change and other parameters. Returns are measured in Bangladeshi taka. (US$1 = Tk 116.42 as of August 4, 2024.)

farmer-specific effects, the only statistically significant marginal productivity effect of HY varieties is days of water shortage. This implies that the unavailability of irrigation in times of need adversely affects rice yield. Bangladeshi farmers generally use diesel or electrically operated irrigation pumps. Thus, a power failure or unavailability of diesel could limit timely irrigation. The other marginal yield effects of HY varieties are not statistically significantly different from 0. Marginal yield gain from land area under HY varieties has a positive impact (i.e., an increase in land area would increase yield). The marginal yield gain of nonharvest labor days is negative, suggesting more labor days are used for HY varieties, contributing to lower yield gains and diminishing returns. However, since experience has a positive estimated effect on the marginal labor productivity of HY varieties, this could probably be interpreted as a learning-by-doing effect. The rich soil estimate implies an additional expected yield of 53.89 kg/acre. The fertilizer estimate implies that one additional kilogram of fertilizer application would increase the expected yield of the HY variety by about 0.03 kg/acre (Table 3).[7]

Tables 5 and 6 report the estimated difference in mean and variance of gross returns, respectively, under HY varieties. Here, we considered all the cost and return variables for the estimates. Base returns change was about Tk 44,704—more than 5 times higher than the restricted random effects model. The only statistically significant variables were experience and days of water shortage. Farmers cultivate

[7] Although these values are not significant, we have reported them based on the recent study by Amrhein, Greenland, and McShane (2019).

Table 6. Estimated Difference in Variance of Returns Under High-Yielding Varieties (N = 659)

Variables	Unrestricted Random Effects Model 1	Differential Yield Model 2	Restricted Random Effects Model 3
Base productivity change	69,896	−571,585	−571,580***
	(117,951)	(444,262)	(88,182)
Marginal yield changes land (Tk/acre)	20,418	150,243	150,243
	(45,779)	(122,470)	
Nonharvest labor cost (Tk/acre)	−4.68	26.63	26.63
	(9.33)	(26.13)	
Experience (years)	−4, 645.95	8,537.43	8,537.43
	(3,556)	(9,879.78)	
Rich soils (dummy)	−60,847	285,498	285,498
	(47,651)	(259,553)	
Fertilizer application cost (Tk/acre)	4.42	−9.82	−9.82
	(8.90)	(24.70)	
Days of water shortage	61,234	−176,894	−176,894
	(54,731)	(154,223)	
Irrigation cost (Tk/acre)	5.13	8.3	8.3
	(5.89)	(22.80)	
Insecticide/pesticide cost (Tk/acre)	65.85*	172.63	172.63
	(36.61)	(131.10)	
R^2	0.02	0.02	

Notes: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses are standard errors. Columns 1, 2, and 3 show the regression results for the variance of gross returns associated with the unrestricted random effects model, the differential yield model, and the restricted random effects model, respectively. The unrestricted random effects model fails to control for farm- and farmer-specific characteristics. Therefore, these estimates are biased and inconsistent. The differential yield model estimates Model 5 and considers the difference in yield between high-yielding (HY) and traditional varieties (TV). The restricted random effects model provides a consistent estimate of base productivity change and other parameters. Returns are measured in Bangladeshi taka. (US$1 = Tk 116.42 as of August 4, 2024.)

the same land following the same repeated production practices; as a result, experience does not help increase yield. Days of water shortage show negative effects on returns. Higher land area under HY rice production would not significantly improve returns. Nonharvest labor costs, irrigation costs, and insecticide costs have negative effects on HY returns. These findings might be attributable to the high input prices. Nonetheless, rich soil positively contributes to HY rice returns.

The differential yield and restricted random effect models' base productivity change show a yield about 45% lower than the unrestricted random effects model. The differential return and restricted random effects models provide about 82% lower returns than the unrestricted random effects model. As explained previously, the restricted random effects estimates decompose the unconditional observed yield and return gains.

Table 7 presents the contributions of each variable to the changes in yield and returns. The base productivity effect was 100.6% due to the adoption of HY varieties. HY cultivation experience has a −30.47% effect. Moreover, land, labor, and fertilizer have a combined −8.79% effect, 61.34% of total base productivity gains. This is mainly because of the lack of proper information. Mottaleb, Rahut, and Erenstein (2019) find that farmers who rely on the recommendations of the government extension agents and their own experience and peer suggestions applied more fertilizer than the suggestions received from fertilizer traders. Peer farmers and pesticide sellers are key sources of pest

Table 7. Decomposition of Expected Output and Return Gains by Source

Variable	Mean Gains Attributable to Variable (%)
Mean HY variety output gains due to HY variety method, of which	**61.34**
Unconditional productivity gains from	
Base productivity effect	100.60
Experience with HY varieties	−30.47
Marginal yield gains from	
Land	0.008
Labor	8.74
Fertilizer	0.04
Plot-specific characteristic (soil)	**3.08**
Farmer-specific effects	**35.58**
Mean HY variety return gains due to HY variety method, of which	**78.68**
Unconditional gains in gross returns from	
Base net returns effect	154.03
Experience with HY varieties	−26.30
Marginal gross returns gains from	
Land	0.05
Labor cost	5.62
Fertilizer cost	13.98
Irrigation cost	12.14
Insecticide cost	17.26
Plot-specific characteristic (soil)	**31.63**
Farmer-specific effects	**−10.31**

Notes: Productivity gain is calculated by adding the experience effect with base productivity change and subtracting the marginal yield gains from different inputs as well as plot-specific characteristics. HY refers to high-yielding varieties.

management information in Bangladesh (Alam and Wolff, 2016). In our analysis, it seems reasonable that the farmers received information from the government agents and/or utilized inputs from their own experience. As a result, experience, education, and training negatively affect the differential gain. Plot-specific characteristics (e.g., rich soil) have a 3.08% effect on productivity gain, while farmer-specific characteristics (e.g., education and training) have a total effect of 35.58%. Training on HY technology adoption has positive effects. These results are consistent with findings from Barrett et al. (2004). On the lower panel of Table 5, we find a base return increase of about 154.03% due to the adoption of HY technology. This finding is consistent with previous literature, which has suggested that modern rice varieties result in increased profit compared to conventional varieties (Nalley et al., 2009; Mishra et al., 2016; Rahman and Connor, 2022). HY varieties experience has a −26.3% effect. The combined effects of land, labor, fertilizer, irrigation, and insecticide costs add up to about −49.0%. Interestingly, plot-specific characteristics (rich soil) have more effect in the returns model (31.63%) than in the differential yield model. However, farmer-specific characteristics have a −10.31% effect on HY return. Our return model included cost and return variables for respective yield and inputs. Farmers' being input/output price takers and the timing of output sales might have contributed to the negative gain from HY varieties.

Production and Return Risk Implications of High-Yielding Varieties

All of the regression results suggest yield risk (see Tables 3–4) and returns risk (see Tables 5–6) decline with the adoption of HY technologies. Further, consistent with previous studies (Abay et al., 2016;

Shahzad and Abdulai, 2021; Varshney et al., 2022), farm household heterogeneity has been found to play a significant role in the pattern of technology adoption. Differenced and restricted random effects models' base risk change parameters suggest that HY technology is less risky than TV technology. Our results differ from previous results in which researchers have indicated HY is riskier than traditional varieties (Barrett et al., 2004; Cavatassi et al., 2011). Our justification is that when useful information is available, farmers use caution and their experience in planting, fertilizer, and water application for HY technology. In the case of TVs, farmers depend on good weather conditions for high yields. This may be due to the fact that the farmers are experienced with HY technology and use similar improved management practices for TV technology as well. More research is needed to fully understand farmers' risk-management attitudes or behaviors, as Carpenter (2010) notes that some GM technologies have lower yield risks than traditional varieties.

Conclusions

Using data collected by IRRI Bangladesh from their Area-Based Farm Household Survey, we examined the interdependence of HY technology adoption and the attributes of the farm and the farmer in meeting rice self-sufficiency in Bangladesh. Farmers cultivated the same plot using the high-yielding varieties in the Boro season and traditional varieties in the Aman season. This allowed us to control for plot-specific attributes and observed farmer characteristics. Regional heterogeneity was found to play a significant role in the pattern of technology adoption. Farmers applied best-yield practices in the most fertile parcels as they cultivated the same plot using two different seed varieties. We acknowledge that unobserved plot and farmer characteristics could shape the adoption decision, but the differential function approach addresses those similar but unobserved characteristics.

We used a method to estimate yield differentials, return differentials, and risk following the methodology and estimation procedure introduced by Barrett et al. (2004). In contrast to Barrett et al., we also analyzed the base return change estimates, including the costs and returns variables. The unrestricted model implied that base productivity gains were almost twice as high as the restricted random effects model that controlled for observable and unobservable variables. The only statistically significant marginal productivity effect of HY varieties was days of water shortage. The differential yield and restricted random effect models' base productivity change was found to be 45% lower than that of the unrestricted random effect model. Base returns change was about Tk 44,704, more than 5 times higher than obtained from the restricted random effects model. Statistically significant variables were experience and days of water shortage. The differential return and restricted random effect models provided about 82% lower returns than the unrestricted random effects model.

The restricted random effects estimates were used to decompose the unconditional observed yield and return gains. The base productivity gain was 61.34%. Plot-specific attributes (e.g., rich soil) had a 3.08% effect on productivity gain, while farmer-specific characteristics (e.g., education and training) had a total effect of 35.58%. On the other hand, we found a base return increase of about 154.03% due to HY technology adoption. Land, labor, fertilizer, irrigation, and insecticide costs had combined effects of about −49.05%. Interestingly, plot-specific attributes had a higher effect (31.63%) on the return model than the differential yield model. However, farmer-specific characteristics had negative (−10.31%) effects on HY return gain. We acknowledged that the accuracy of these effects is likely to improve when analyzing recent data, while the overall findings can be expected to remain the same.

The differenced and restricted random effects models' base risk change parameters suggest HY technology is less risky than TV technology. These results contradict the findings of Barrett et al. (2004), who studied rice cultivation situations in Madagascar. Our results might be due to the fact that the farmers were experienced in adopting HY technology and had similar improved management practices for TV technology.

This study has several practical implications. First, we found that farmers' characteristics (e.g., education, training) were responsible for an unconditional yield gain of about 36%. The findings of this study could be helpful in promoting the adoption of other agricultural technologies (e.g., HY varieties for wheat and improved varieties of fish, cattle, fruits, and vegetables) in Bangladesh to ensure farmers' food security. Second, the gains in unconditional returns from farmer-related characteristics were negative, but these characteristics positively related to yield changes. This may suggest that the increased labor required to learn and adapt to new farming technologies limited their adoption. Additionally, farmers are price takers and do not control the prices of their inputs and outputs. Due to a lack of proper storage facilities and immediate household needs, Bangladeshi farmers typically sell rice immediately after the harvest to cover debt obligations and household expenses. If institutional credit availability increases and the government sets a price floor, farmers may store agricultural products and benefit from better timing of sales. Setting up a price floor could help rice producers overcome the low prices that are prevalent immediately after the harvest.

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