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

Mohammad R. Hasan, Krishna P. Paudel, Madhav Regmi, Maria Bampasidou, Humnath Bhandari, and Stephen Devadoss

We examine the interdependence of high-yielding variety (HYV) technology 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, from an Area-Based Farm Household Survey to estimate yield differentials, return differentials, and risk. We find that HYV rice varieties contributed to 61.34 percent, plot-specific attributes contributed to 3.08 percent, and farmer-specific characteristics contributed to 35.58 percent toward rice productivity. Additionally, adopting HYV technology resulted in a base return increase of about 154.03 percent. However, land, labor, fertilizer, irrigation, and insecticide costs had combined negative effects of approximately 49.05 percent on the return model. Plot-specific attributes had more effects on the return model than on the differential yield model, while farmer-specific characteristics had a negative effect on HYV return gain. Results also show that HYV technology is less risky compared to the traditional variety (TV) technology.

Key words: farm/farmer characteristics, restricted/unrestricted yield gain, rice production, self-sufficiency

Introduction

Food security and food self-sufficiency are interrelated concepts, although food self-sufficiency is not required for food security. The FAO (1996) defines food security as a situation when 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 the concept where a country produces a sufficient amount of food to feed its population. Producing

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Hasan is a professor of economics at Hajee Mohammad Danesh Science and Technology University, Dinajpur-5200, Bangladesh. Paudel (Krishna.paudel@usda.gov) is the Deputy Director for Research and Communications, Resource and Rural Economics Division, United States Department of Agriculture Economic Research Service, Washington, D.C. Regmi is an assistant professor in the Department of Agricultural Economics and Agribusiness, New Mexico State University, Las Cruses, New Mexico. Bampasidou is an associate professor in the Department of Agricultural Economics and Agribusiness, Louisiana State University (LSU) and LSU Agricultural Center, Baton Rouge, Louisiana. Bhandari is an Agricultural and Environmental Economist at the International Rice Research Institute, Bangladesh. Devadoss is an Emabeth Thompson Endowed Professor in the Department of Agricultural and Applied Economics, Texas Tech University, Lubbock, Texas.
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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. Yet, food self-sufficiency has been the goal for staple food crops (e.g., rice self-sufficiency goal in the Philippines, Indonesia, and China) in many countries (Warr and Yusuf, 2014). These countries aim to be self-sufficient in staple food crop production by increasing agricultural productivity, increasing crop areas with high-yielding 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 and re-emergence 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 (Chandino et al., 2022; Fuglie & Echeverria, 2024; Souza et al., 2020), economic gains (Walton et al., 2008), social advantages (Boyer et al., 2016; Fuglie & Echeverria, 2024), and environmental improvements (Huffman et al., 2017; Chandino et al., 2022). For instance, mechanization in agriculture has significantly increased rice productivity in China (Chandino et al., 2022). Fuglie and Echeverria (2024) find that various agricultural technologies 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 U.S. apple producers. Similarly, adopting GM corn has been shown to increase productivity and reduce environmental degradation by improving soil moisture content (Huffman et al., 2017). It is also worth noting that the Green Revolution and high-yielding 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 their 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 et al., 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; Conley and Udry, 2010), and price risk (Liu, 2013; Ward and Singh, 2013). 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 examined are education and social network (Huffman, 2001; Skinner and Staiger, 2007), input utilization (Duflo et al., 2008), risk preferences (Sunding and Zilberman, 2001; Dercon and Christiansen, 2011), and seed trait preferences (Useche et al., 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, not due to the features of the new technology (for example, seed traits, fertilizer, machinery), but rather due to the farmers' attributes (for example, farmer's education, farmer's training on new technologies) and farmer cultivation practices (for example farmers being early adopters, farmers selecting labor-saving technologies) (Huffman, 2001; Barrett et al., 2004; Useche et al., 2009). Studies have also reported that regional heterogeneity can affect technology adoption (Useche et al., 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. The survey includes information on adopters and nonadopters of the HYV technology. We employ 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 the HYV technology for one season and using traditional rice varieties for the other season. This way, we control to a larger extent for plot and farmer heterogeneity, allowing us to gain further insight into what drives these differentials. In addition, we quantify differential returns and cost functions.

Improved high-yielding varieties of rice seeds, subsidized fertilizer, infrastructural 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, although quite late compared to India or Mexico (Sonnenfield, 1992; Hossain, Bose, and Mustafi, 2006). Despite an increase in population and a decrease in arable land, adopting these technologies over the last decade helped accelerate the production of food grains in the country, with Bangladesh almost achieving self-sufficiency in rice production (FAOSTAT, 2015). This is why Bangladesh is ideal for researching the role of improved farming technologies in achieving food self-sufficiency. Furthermore, 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). It is worth noting that the country had a population of 168 million in 2022, which is expected to increase to 186 million by 2030. Therefore, it is crucial to identify both the factors affecting rice production technologies and their role in food sufficiency in Bangladesh.

The empirical results indicate that the HYV technology application generated an estimated increase in rice yield by 61.34 percent. An estimated 35.58 percent was attributed to individual rice grower characteristics adding to the literature that highlights the interrelation of farmer characteristics and technology adoption decisions. Lastly, an estimated yield increase of 3.08 percent was attributed to plot attributes. Similarly, our analysis of differential return function estimates showed that the return increase was caused by HYV adoption (78.68 percent), plot attributes (31.63 percent), and farmer characteristics (-10.31 percent). By quantifying the role of high-yielding varieties (HYV), 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 HYV 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 et al., 2019).

Rice is a staple food item in Bangladesh. Rice varieties are planted in three seasons: aman, which is cultivated during the "wet" season beginning from mid-July to mid-November; boro, which is cultivated during the "dry" season beginning from mid-November to mid-March; and aus, the spring season variety cultivated from mid-March to mid-July (FAO, 2019). Aman season rice consists of mainly traditional rice varieties that are rainfed and require less fertilizer; those rice varieties are susceptible to drought as well as flood (Asaduzzaman et al., 2010). High-yielding boro 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 et al., 2019). The last variety, aus, has been sparsely cultivated during the last few decades (Asaduzzaman et al., 2010).

With trade liberalization on importing small-scale irrigation equipment (Mottaleb et al., 2017; Mottaleb et al., 2019) and intensive use of chemical fertilizer HYV/ modern varieties (MV) covered about 85 of the total rice area in 2016-17, while it was only about 15 percent in 1981-82 (BRRI, 2018; Mottaleb et al., 2019). With the increase in population, per capita cultivable area has been declining since the 1960s (Mottaleb et al., 2019). In 2013, per capita arable land was about 0.005 hectares, while it was 0.17 hectares in 1961 (World Bank, 2017; Mottaleb et al., 2019). In 1982, the net cultivable area was about 9.83 million hectares. It declined dramatically to 8.7 million hectares by 1992-93, and the total cultivable land was 7.77 million hectares by 2008-2009 (Alam and Islam, 2013).

Changes in government policies, which favored privatization in the procurement and distribution of small-scale irrigation equipment and chemical fertilizers, liberalization of trade, and reduction in tariff for imported agricultural equipment, were also factors that complemented the HYV adoption (Mottaleb et al. 2017; Mottaleb et al., 2019). Private investment in small-scale irrigation equipment was considered a dominant factor in facilitating the diffusion of HYVs (Asaduzzaman et al., 2010; Mottaleb et al., 2017; Mottaleb et al., 2019). As a result, farmers invested substantially in shallow tube wells and power pumps, contributing to rapidly expanding irrigation facilities. The diffusion of HYV boro rice is strongly related to the expansion of groundwater irrigation (Asaduzzaman et al., 2010; Mottaleb et al., 2019). Moreover, 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).

The upward trends in rice cultivation area, yield, and production volume in Bangladesh have been noticeable since adopting HYVs (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 percent per year growth rate (Alam and Islam, 2013; Ricepedia, 2019). Bangladesh almost achieved self-sufficiency in 2016, but extreme weather events in 2017 (such as heavy monsoon that led to the flooding of major rice areas Dhaka and Rajshahi) resulted in a lower total (USDA, 2017; USDA 2018) production, though in 2018, the country produced a surplus amount of rice.[1] The yield of traditional varieties (TVs) has also increased from 1.52 tons/ha in 1965 to 2.14 tons/ha by 2009, a growth rate of 0.9 percent per year (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 rice grown in the lowest-yielding season aus (Hossain et al., 2003).

[1] In 2018, total rice production in Bangladesh exceeded by seven million tons than the domestic needs. USDA forecasts rice harvested area and production in Bangladesh for the marketing year 2021/2022 to be at 11.62 million hectares and 3.59 million metric tons, slightly up from the previous marketing year. The government of Bangladesh continues to import rice to make it affordable. It is estimated that Bangladesh will import 1.5 million metric tons of rice in MY 2021/2022. Source: https://www.fas.usda.gov/data/bangladesh-grain-and-feed-update-22

Method

Several studies examined the adoption of agricultural innovation, considering the diverse characteristics of farmers, farms, and farming regions in an empirical setting. For example, Abay et al. (2016) explored the adoption of fertilizer, seed, and extension services, considering farm household-level unobserved heterogeneity such as risk-taking and technology preferences. Tran-Nam and Tiet (2022) determined the socio-demographic determinants of organic farming adoption accounting for individual heterogeneity in environmental belief. Varshney et al. (2022) examined the adoption of hybrid mustard in India, considering the heterogeneity across different casts of farm producers. Barnes et al. (2019) considered 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) examined the adoption of climate-smart agricultural technology in Pakistan, 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 and Zilberman, 1985; Ruzzante et al., 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 the HYV 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 (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 considering 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, the 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 HYV and TV, we define the respective yield function; $y_f = y_f(x, z)$ for HYV and $y_g = y_g(x, z)$ for TV. Each technology is characterized by a vector of production inputs (x) controlled by the farmer and a vector of exogenous characteristics related to farm, farmer, and environmental conditions (z). For our study, vector x contains information on land use, labor usage and labor cost, fertilizer application and fertilizer cost, pesticide cost, herbicide cost, and irrigation cost. Vector 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 HYV, 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.

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[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 the two approaches and based on the scenario we examined we believe that the best approach is to employ a primal model. Dual is not efficient because it fails to utilize all the available information (Mundlak, 1996).

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

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

$$\text{HYV: } y_f = f(x,z) + h_f(x,z)^{\frac{1}{2}}\xi_f \ldots\ldots\ldots\ldots\ (1)$$

$$\text{TV: } y_g = g(x,z) + h_g(x,z)^{-\frac{1}{2}}\xi_g \ldots\ldots\ldots\ldots\ (2)$$

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

$$E[y_f] = \alpha_{f0} + \sum_{i=1}^{r} \alpha_{fi}\, x_{fi} + \sum_{i=1}^{r}\sum_{j=1\neq i}^{r} \beta_{fij} x_{fi} x_{fj} + \sum_{i=1}^{t} \gamma_{fi}\, z_{fi} + \sum_{i=1}^{t}\sum_{j=1\neq i}^{t} \eta_{fi}\, z_{fi} z_{fj} + \sum_{i=1}^{r}\sum_{j=1}^{t} \tau_{fij} x_{fi}\, z_{fj} \ldots\ldots\ldots\ (3)$$

$$E[y_g] = \alpha_{g0} + \sum_{i=1}^{r} \alpha_{gi}\, x_{gi} + \sum_{i=1}^{r}\sum_{j=1\neq i}^{r} \beta_{gij} x_{gi} x_{gj} + \sum_{i=1}^{t} \gamma_{gi}\, Z_{gi} + \sum_{i=1}^{t}\sum_{j=1\neq i}^{t} \eta_{gi}\, z_{gi} z_{gj} + \sum_{i=1}^{r}\sum_{j=1}^{t} \tau_{gij} x_{gi}\, z_{gj} \ldots\ldots\ldots\ (4)$$

To estimate the effect of the technology adoption on yield, we subtract equation (4) from equation (3).

$$dy = \alpha_0 + \sum_{i=1}^{r} \alpha_i\, dx_i + \sum_{i=1}^{r}\sum_{j=1\neq i}^{r} \beta_{ij} dx_i dx_j + \sum_{i=1}^{t} \gamma_i\, dz_i + \sum_{i=1}^{t}\sum_{j=1\neq i}^{t} \eta_{ij}\, dz_i dz_j + \sum_{i=1}^{r}\sum_{j=1}^{t} \tau_{ij} dx_i\, dz_j + d\varepsilon \ldots\ldots\ldots\ (5)$$

where $dy = E[y_f] - E[y_g]$ is the difference in expected output or return, $dx = x_f - x_g$ 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 zero, 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 x and z, we can remove potential bias from omitted but similar unobserved characteristics. Hence, when estimating equation (5), i.e., the difference in expected output or return, we obtain consistent and unbiased estimates of the marginal productivity differences (gains) attributable to the HYV technology. These productivity gains can be decomposed into gains from switching to a better technology, gains related to plot quality, or gains attributed to farmer characteristics. The gains from the marginal productivity of inputs are calculated as the product of the slope parameter estimates from equation (5) and the sample mean of the vector x variables. The same approach is used to calculate plot-attribute specific gains (vector z variables).

[4] Equations (3) and (4) can be converted into a standard regression model by adding a zero mean of normally distributed i.i.d. error term.

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

$$S^2 = V[y_f] - V[y_g] = E[\varepsilon_f^2 - \varepsilon_g^2] = h(x, z) \dots\dots\dots\dots\dots\dots (6)$$

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 x and z vectors. Notice that the variance is a function of the x and z vectors, i.e., 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:

$$s^2 = \theta_0 + \sum_{i=1}^{r} \theta_i x_i + \sum_{i=1}^{r} \sum_{j=1 \neq i}^{r} \lambda_{ij} x_i x_j + \sum_{i=1}^{t} \varphi_i z_i + \sum_{i=1}^{t} \sum_{j=1 \neq i}^{t} \delta_{ij} z_i z_j + \sum_{i=1}^{r} \sum_{j=1}^{t} \omega_{ij} x_i z_j + \psi \dots\dots (7)$$

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 as well as 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 (Barret et al., 2004). The method used, including the estimation of the production function instead of the profit function, as indicated by (Barret et al., 2004), "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) argued that Barrett et al. (2004) approach "provides a biased estimate of the true base productivity gains associated with the new technology." It is because the parameter in equation 6, without correction, "incorporates output gains associated with adopters' observable and unobservable attributes that may not be replicable in the broader population of nonadopters" (Chen and Yen, 2006). Thus, we considered the corrections for equal slope coefficient and cross-product terms in Barrett et al. (2004), 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 assume the first one of 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.

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 pre-tested survey questionnaire was used, and data collection was conducted by the trained enumerators covering 18 districts of Bangladesh.

Our dataset comprises 659 observations based on farmers who cultivated both HYV and TV rice varieties in 2014. Initially, there were 740 observations, and 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 keep up consistency with Barrett et al. (2004), we did not consider regional (district) variations. We isolate responses from farmers (household heads) who cultivated both HYV and TV rice varieties during the boro and aman seasons, respectively. As mentioned earlier, HYVs 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.

The first panel in 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 percent of the farm operators were male, and 81 percent of farm operators received training in HYV rice cultivation methods through local extension agents. About 34 percent of the farmers had no formal education, while 22.75 percent had received at least a high school education. The average education level of the farm operators was about five 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 a cropped area of 0.98 acres (2.47 acres = 1 hectare). Considering two major rice-growing seasons, about 52 percent of the total area under rice production was done using HYVs. About 44 percent of the farmers own a tractor/power tiller and/or diesel or electricity-operated tube wells.

The second panel presents information on the two rice cultivation practices examined in this study, namely HYV and TV. On average, the farm size used for rice cultivation was about 0.49 acres each season (two seasons, so the effective area was 0.49*2 = 0.98 acres). On average, 0.49 acres were cultivated with HYV 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 nine years of experience with the HYV 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, the HYVs were introduced in the mid-1980s in Bangladesh, and based on our sample, we

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

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

Rice Cultivation Methods	**HYV**			**TV**		
	Mean	**Min**	**Max**	**Mean**	**Min**	**Max**
Mean area of plot (acre)	0.49	0.04	2.70	0.48	0.05	2.97
(Standard Deviation)	(41.55)			(35.82)		
Mean years of experience with	8.51	2	22	28.40	2	76
method	(3.69)			(12.22)		
(Standard Deviation)	1.90	1	2	1.74	1	2
Mean days of water shortage in	(0.30)			(0.43)		
field	70.23			70.23		
(Standard Deviation)	100			100		
Percent of fields on rich soils	2155	420	3,800	931	222	2960
Percent using chemical fertilizer	(432)			(436)		
Mean yield (kg/ac)						
(Standard Deviation)						

Returns and Prices						
Return from HYV rice (tk/ac)	37040.23	6062	108771	31909	4380	184800
(Standard Deviation)	(10754)			(21184)		
Price of rice (tk/kg)	17.16	10	39	34.34	10	73
(Standard Deviation)	(3.41)			(13.58)		

Note: TV and HYV respectively refer to "traditional varieties" and "high-yielding varieties."

Table 2. Productivity of Land and Labor

	HYV		**TV**		**Mean Difference (percent)**	
	Yield (kg/ac)	**Return (tk/ac)**	**Yield (kg/ac)**	**Return (tk/ac)**	**Yield**	**Return**
Output/Return	2,154 (432)	37,040 (10,754)	931 (436)	31,909 (21,184)	131	16
Labor productivity	146	11.22	128	17.90	14	-37
Non-harvest labor	14.75 (15.06)	3,299 (2,059)	7.24 (10.18)	1,782 (1,432)	103	85

Note: Figures in the parentheses represent standard deviation. TV and HYV refer to "traditional varieties" and "high-yielding varieties," respectively. Returns are measured in taka (US$1 = 116.42 Bangladeshi taka (tk) as of 08/04/2024).

see that the adoption of HYVs is a continuous and ongoing process. Despite the introduction of the HYVs, the average area under HYV rice plots and TV rice plots 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] The alluvial land is highly fertile and suitable for rice cultivation. The surveyed farmers reported that 70 percent 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 HYV yield was about 2,155 kilogram (kg) per acre (ac), while it was about 931 kg/ac for the TV. The maximum HYV yield was 3,800 kg/ac, while it was 2,960 kg/ac for TV.

The last panel of Table 1 represents returns and prices of rice yields in Bangladesh for both technologies and seasons. The average return on HYV rice production was about 37,040 taka per acre (tk/ac)[6] , with a maximum of 108,771 tk/acre and a minimum of 6,062 tk/acre. On average, the return on TV rice production was about 31,909 tk/acre, with a maximum of 184,800 tk/acre and a minimum of 4380 tk/acre. The average returns were almost similar because of the prices. The average price for HYV rice was about 17 tk/kg, while it was about 34 tk/kg for TV rice. This price difference is attributed to rice quality; that is, HYVs are mostly coarse grain and are used for home consumption by farmers year-round. TVs are mostly aromatic with fine grains, and as a result, farmers earn a higher price compared to the price of HYVs. 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 10 tk to over 70 tk per kilogram within a year. There is no operating futures market in the country, but the farmers can get higher prices if they sell outside of the immediate harvesting time. It's 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 non-harvest labor are measured in terms of both physical and monetary terms. Physical output is measured in kilogram per acre (kg/ac) and returns are measured in taka per acre (tk/ac). Labor productivity is calculated by dividing the outputs and returns by non-harvest labor days and the cost of non-harvest labor. Non-harvest labor is measured in both man-days and taka per acre.

[5] These two rivers are known as Padma and Jamuna, respectively, in Bangladesh.
[6] Note: US$1 = 116.42 Bangladeshi taka (tk) as of 08/04/2024, Source: https://www.xe.com/currencyconverter/convert/?Amount=1&From=USD&To=BDT

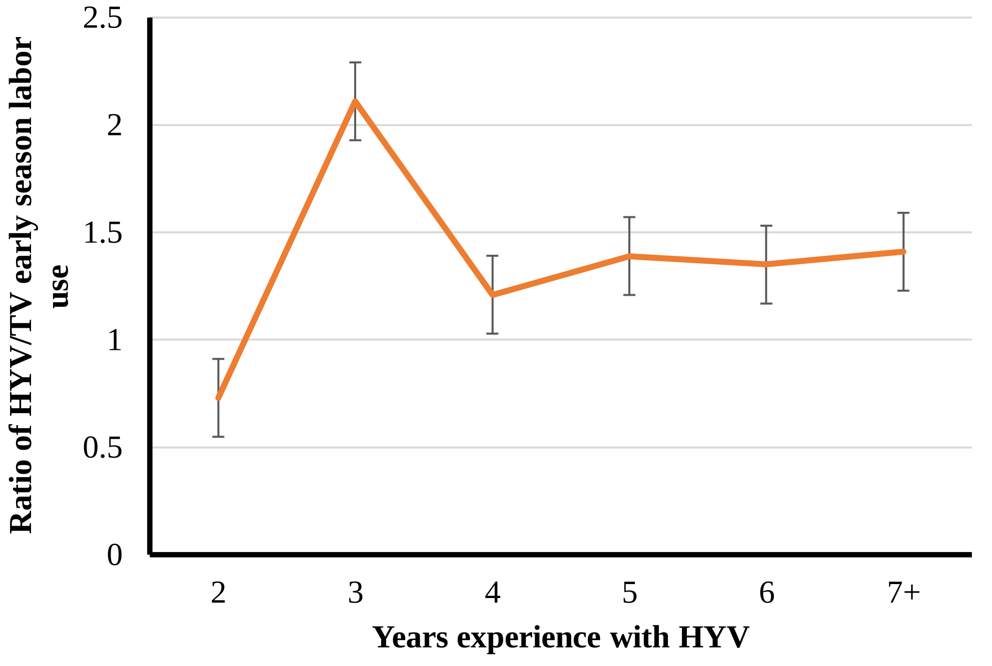

Figure 1. Median and span of labor use ratio

Results show that HYV plots have a 231 percent higher yield than TV plots, while in terms of returns, it is only about 16 percent higher. 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). Physical output varies more under TV than under HYV, while it is the opposite for returns based on the standard deviation (SD) value shown inside parentheses. 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 the farmers' needs and desires, specifically whether they sell immediately after harvesting or store rice for future sales. The use of non-harvest labor days for HYV is almost double that of the non-harvest 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 HYV compared to TV then the ratio of (HYV/TV) labor utilization decreases and remains slightly above 1 for the remaining periods. With increased experience with HYV, after about four years, the ratio of HYV 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.

Table 3. Estimated Difference in Mean Rice Yields under HYV

	Model		
Mean Yield (kg/ac)	Unrestricted Random Effects	Differential Yield	Restricted Random Effects
Base productivity change	2,235***	1,230***	1,230.52***
	(132.54)	(69.33)	(24.33)
Marginal yield changes land (ac)	48.18	98.11	*98.11*
	(103.67)	(79.34)	
Non-harvest labor (days/ac)	-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/ac)	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-squared	0.02	0.02	-
N	659	659	

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Columns 2, 3, and 4 of Table 3 show the regression results for mean rice yield (kg/ac), respectively, associated with the unrestricted random effects model, differential yield model, and restricted random effects model. The common independent variables in these models include base productivity change, marginal yield changes land (ac), non-harvest labor (days/ac), experience (years), rich soils (dummy), fertilizer application (kg/ac), days of water shortage, interaction of land and experience, and interaction of labor and experience. The unrestricted random effects model fails to control for farm and farmer specific characteristics. Therefore, these estimates are biased and inconsistent. Differential yield estimates the model (5) and considers the difference in yield between high-yielding varieties (HYVs) and traditional varieties (TVs). Restricted random effects provide a consistent estimate of base productivity change and other parameters.

Results and Discussions

Tables 3-6 report the regression results for rice yield (kg/ac) and returns (tk/ac), respectively. In both tables, the left-hand column 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. The middle columns display the differential yield function estimates from equation (5). The marginal yield effect estimates are consistent, but the base productivity gain is not consistent. That is, the parameter estimates of each explanatory variable (land, labor, experience, etc.) are consistent, while the constant (base productivity change) is not consistent. The right-hand columns report the corrected base productivity change estimate from the restricted random effects. For the restricted random effects, the slopes are

Table 4. Estimated Difference in Variance of Rice Yields under HYV

Variance of Yields	Model Unrestricted Random Effects	Differential Yield	Restricted Random Effects
Base productivity change	89.53 (156.11)	-42.70 (118.47)	-42.72 (34.53)
Marginal yield changes land (ac)	-269.91** (105.54)	240.14*** (91.99)	*240.14****
Non-harvest labor (days/ac)	0.93 (5.05)	0.87 (6.61)	*0.87*
Experience (years)	-8.69 (13.51)	4.85 (3.67)	*4.85*
Rich soils (dummy)	32.69 (40.60)	163.55** (86.46)	*163.55***
Fertilizer application (kg/ac)	0.09 (0.46)	0.69 (0.46)	*0.69*
Days of water shortage	100.16** (49.10)	19.06 (65.97)	*19.06*
Land × experience	36.61*** (13.86)	5.29 (4.75)	*5.29*
Labor × experience	0.13 (0.68)	0.01 (0.27)	*0.01*
R-squared	0.02	0.02	-
N	659	659	

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Columns 2, 3, and 4 of Table 4 show the regression results for the variance of rice yield, respectively, associated with the unrestricted random effects model, differential yield model, and restricted random effects model. The common independent variables in these models include base productivity change, marginal yield changes land (ac), non-harvest labor (days/ac), experience (years), rich soils (dummy), fertilizer application (kg/ac), days of water shortage, interaction of land and experience, and interaction of labor and experience. The unrestricted random effects model fails to control for farm and farmer specific characteristics. Therefore, these estimates are biased and inconsistent. Differential yield estimates the model (5) and considers the difference in yield between high-yielding varieties (HYVs) and traditional varieties (TVs). Restricted random effects provide a consistent estimate of base productivity change and other parameters.

restricted to equal the estimates generated by the preceding differential yield function (the middle columns of Tables 3-6, respectively).

Tables 3 and 4 show the estimated difference in mean and variance of yields of high-yielding varieties. Results indicate that base productivity gains are almost two times higher 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 found the estimate to be 84 percent higher. This could imply that the farmers use similar inputs for both varieties. Once we difference away farm- and farmer-specific effects, the only statistically significant marginal productivity effect of HYV 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, the

Table 5. Estimated Difference in Mean Returns under HYV

Mean Returns (tk/ac)	Model		
	Unrestricted Random Effects	Differential Returns	Restricted Random Effects
Base productivity change	44,704*** (2693)	7,904.6** (3118)	7,903.5*** (908)
Marginal yield changes land (taka/ac)	-1,269.86 (1106)	2,577 (1710)	*2,577*
Non-harvest labor cost (taka/ac)	-0.08 (0.21)	-0.20 (0.41)	*-0.20*
Experience (taka/yr)	-263.25** (103.4)	67.85 (84.32)	*67.85*
Rich soils (dummy)	275.37 (1046)	2319.8 (2170)	*2319.8*
Fertilizer application cost (taka/ac)	0.19 (0.18)	-0.38 (0.34)	*-0.38*
Days of water shortage	-2,537.81** (1179)	-3,573.9** (1676.7)	*-3,573.9***
Irrigation cost (taka/ac)	-0.02 (0.14)	-0.13 (0.30)	*-0.13*
Insecticide/pesticide cost (taka/ac)	-0.89 (0.88)	-1.83 (1.75)	*-1.83*
R-squared	0.02	0.02	-
N	659	659	

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Columns 2, 3, and 4 of Table 5 show the regression results for average returns (tk/ac), respectively, associated with the unrestricted random effects model, differential yield model, and restricted random effects model. The common independent variables in these models base productivity change, marginal yield changes land (tk/ac), non-harvest labor cost (taka/ac), experience (taka/yr), rich soils (dummy), fertilizer application cost (tk/ac), days of water shortage, irrigation cost (taka/ac), and insecticide/pesticide cost (tk/ac). The unrestricted random effects model fails to control for farm and farmer specific characteristics. Differential return estimates a model similar to (5) for return and considers the difference in return between high-yielding varieties (HYVs) and traditional varieties (TVs). Restricted random effects provide consistent estimates of base productivity change and other parameters.

power failure or unavailability of diesel could limit timely irrigation. The other marginal yield effects of HYV are not statistically significantly different from zero. Marginal yield gain from land area under HYV has a positive impact; that is, an increase in land area would increase the yield. The marginal yield gain of non-harvest labor days is negative, suggesting higher labor days application for HYV. However, since experience has a positive estimated effect on the marginal labor productivity of HYV, this could probably be interpreted as a learning-by-doing effect. Rich soil estimate implies an additional expected yield of 53.89 kg per acre. The fertilizer estimate implies that one additional kilogram of fertilizer application would increase the expected HYV yield by about 0.03 kilograms per acre (Table 3).[7]

[7] Although these values are not significant, we have reported them based on the recent article in *Nature* by Amrhein, Greenland and McShane (2019). See https://www.nature.com/articles/d41586-019-00857-9

Table 6. Estimated Difference in Variance of Returns under HYV

	Model		
Variance of Returns	Unrestricted Random Effects	Differential Returns	Restricted Random Effects
Base productivity change	69,896 (117,951)	-571,585 (444,262)	-571,580*** (88,182)
Marginal yield changes land (taka/ac)	20,418 (45,779)	150,243 (122,470)	*150,243*
Non-harvest labor cost (taka/ac)	-4.68 (9.33)	26.63 (26.13)	*26.63*
Experience (taka/yr)	-4645.95 (3556)	8,537.43 (9879.78)	*8,537.43*
Rich soils (dummy)	-60,847 (47,651)	285,498 (259,553)	*285,498*
Fertilizer application cost (taka/ac)	4.42 (8.90)	-9.82 (24.70)	*-9.82*
Days of water shortage	61,234 (54731)	-176,894 (154223)	*-176,894*
Irrigation cost (taka/ac)	5.13 (5.89)	8.30 (22.80)	*8.30*
Insecticide/pesticide cost (taka/ac)	65.85* (36.61)	172.63 (131.1)	*172.63*
R-squared	0.02	0.02	-
N	659	659	

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Columns 2, 3, and 4 of Table 6 show the regression results for the variance of gross returns, respectively, associated with the unrestricted random effects model, differential yield model, and restricted random effects model. The common independent variables in these models base productivity change, marginal yield changes land (tk/ac), non-harvest labor cost (taka/ac), experience (taka/yr), rich soils (dummy), fertilizer application cost (tk/ac), days of water shortage, irrigation cost (taka/ac), and insecticide/pesticide cost (tk/ac). The unrestricted random effects model fails to control for farm and farmer specific characteristics. Differential return estimates a model similar to (5) for return and considers the difference in return between high-yielding varieties (HYVs) and traditional varieties (TVs). Restricted random effects provide consistent estimates of base productivity change and other parameters.

Tables 5 and 6, respectively, report the estimated difference in mean and variance of gross returns under HYV. Here, we considered all the cost and return variables for the estimates. Base returns change was about 44,704 tk—more than five times higher than the restricted random effects model. The only statistically significant variables were experience and days of water shortage. Farmers cultivate the same land following the same repeated production practices, and, as a result, experience does not help increase yield. Days of water shortage show negative effects on returns. Higher land area under HYV rice production would not significantly improve the returns. Non-harvest labor costs, irrigation costs, and insecticide costs have negative effects on HYV returns. These findings might be attributable to the high input prices. Nonetheless, rich soil positively contributes to the returns of HYV rice.

The differential yield and restricted random effect models' base productivity change shows a yield about 45 percent lower than the unrestricted random effects model. The differential return and restricted random effects models provide about 82 percent lower returns than the unrestricted

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

Percent of Mean HYV Output Gains Due to	**(Percent)**
HYV method, of which	**61.34**
Unconditional productivity gains from	
Base productivity effect	100.6
Experience with HYV	-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**
Percent of Mean HYV Return Gains Due to	
HYV method, of which	**78.68**
Unconditional gains in gross returns from	
Base net returns effect	154.03
Experience with HYV	-26.3
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**

Note: 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 the plot specific characteristics.

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 percent due to the adoption of HYV. HYV cultivation experience has a 30.47 percent negative effect. Moreover, land, labor, and fertilizer have a combined 8.79 percent negative effect, 61.34 percent of total base productivity gains. This is mainly because of the lack of proper information. Mottaleb et al. (2019) found 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 management information in Bangladesh (Alam and Wolf, 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, such as rich soil, have a 3.08 percent effect on productivity gain, while farmer-specific characteristics, such as education and training, have a total effect of 35.58 percent. Training on HYV technology adoption has positive effects. These results are consistent with Barrett et al. (2004) findings. On the lower panel of Table 5, we find a base return increase of about 154.03 percent due to the adoption of HYV technology. This finding is consistent with previous literature, which suggested that modern rice varieties result in increased profit compared to conventional varieties (Nalley et al., 2009; Mishra et al., 2016; Rahman and Conner, 2022).

HYV experience has a 26.3 percent negative effect. The combined effects of land, labor, fertilizer, irrigation, and insecticide costs add up to about negative 49.05 percent. Interestingly, plot-specific characteristics (rich soil) have more effect in the returns model (31.63 percent) than in the differential yield model. However, farmer-specific characteristics have a negative (10.31 percent) effect on HYV 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 HYV.

The Production and Return Risk Implications of HYV

All of the regression results suggest yield risk and returns risk decline with the adoption of HYV technologies (see the bottom panel of Tables 3 and 4, respectively). 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 HYV technology is less risky than TV technology. Our results differ from previous results in which researchers have indicated HYV 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 HYV technology. In the case of TV, farmers depend on good weather conditions for high yields. This may be due to the fact that the farmers are well-experienced in adopting the HYV technology and use similar improved management practices for the TV technology as well. In this regard, more research is needed to understand the risk management attitude or behavior of farmers fully. In fact, Carpenter (2010) indicates that some GM technologies are also less risky than TV.

Conclusions

We examined the interdependence of HYV technology adoption and the attributes of the farm and the farmer in meeting rice self-sufficiency in Bangladesh. We used data collected by IRRI Bangladesh from an Area-Based Farm Household Survey. 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 the 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. (2004), 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 HYV was days of water shortage. The differential yield and restricted random effect models' base productivity change was found to be 45 percent lower than that of the unrestricted random effect model. Base returns change was about 44,704 taka, more than five 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 percent 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 percent. Plot-specific attributes, such as rich soil, had a 3.08 percent effect on productivity gain, while farmer-specific characteristics, such as education and training, had a total effect of 35.58 percent. On the other hand, we found a base return increase of about 154.03 percent due to HYV technology adoption. Land, labor, fertilizer, irrigation, and insecticide costs had combined effects of about -49.05 percent. Interestingly, plot-specific attributes (rich soil) had more effects (31.63 percent) on the return model than the differential yield model. However, farmer-specific characteristics had negative (-10.31 percent) effects on HYV 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 HYV 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 the HYV technology and had similar improved management practices for TV technology.

This study has several practical implications. First, we found that farmers' characteristics (education, training) were responsible for an unconditional yield gain of about 36 percent. In this aspect, the findings of this study could be helpful in promoting the adoption of other agricultural technologies, such as HYV 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, while 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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