Are small-scale rice farmers in eastern India really inefficient? Examining the effects of microtopography on technical efficiency estimates

Nobuhiko Fuwa[a*], Christopher Edmonds [b], Pabitra Banik [c]

[a] *Agricultural Economics, Chiba University, 648 Matsudo, Matsudo-City, Chiba. 271-8510 Japan*

[b] *Asian Development Bank, Mandaluyong, Metro Manila, Philippines*

[c] *Agricultural and Ecological Research Unit, Biological Sciences Division, Indian Statistical Institute, Kolkata, India.*

Received 15 November 2005; received in revised form 31 May 2006; accepted 3 January 2007

Abstract

The article analyzes how controlling for differences in land types (defined by position on a low scale toposequence) affects estimates of farm technical efficiency for rice farms in eastern India. Contrasting previous research, we find that farms are considerably more technically efficient when efficiency estimates are carried out at the plot level and control for plot characteristics rather than at the farm level without such controls. Estimates show farms cultivating modern varieties are technically efficient, and plots planted with traditional varieties on less productive lands (upland and mid-upland) operate close to the production frontier. Significant technical inefficiency is found on more productive lands (medium and lowland plots) planted with traditional rice varieties. The finding that these smallholder rain-fed rice farms are efficient cultivators on some plots contrasts with previous findings of farm-level inefficiency (i.e., rejects overarching explanations linked to farm operator ignorance or lack of motivation) and suggests more complex explanations are required to address the inefficiency that is present.

JEL Classification: O13, O33, Q12, Q16

---

* Corresponding author. Tel./fax: 81 47 308 8932.
E-mail address: nfuwa@faculty.chiba-u.jp (N. Fuwa)

Keywords: Technical efficiency; Stochastic frontier production function; Productivity; Rice; India

1. Introduction

The diffusion and adoption of green revolution technologies for rice and wheat has proceeded slowly in two extensive agricultural regions in India: the dry semi-arid tropics and the eastern India's rice-growing region (Walker and Ryan 1990). This article focuses on small-scale rice farmers in the Chhotanagpur Plateau in eastern India, an area characterized by its high poverty incidence and large share of households with scheduled tribe ethnic backgrounds, low productivity in largely rain-fed agriculture, and an environmentally degraded landscape with an undulating topography.

Among the crucial questions facing policy makers in eastern India is: what should investment priorities be in efforts to improve the agricultural productivity of small farms, and through this, the living standards of impoverished households that derive a significant share of their income from agriculture? We address this question by estimating the degree of technical efficiency among a sample of farm-households in eastern India. For example, better understanding of the local farming system of farm efficiency in rice production—the main food staple and dominant crop in the area—and of the farm characteristics associated with greater or lesser technical efficiency can help in the formulation of agricultural development policy for eastern India. A finding that there is substantial technical inefficiency would suggest directing public investments toward measures for improving technical efficiency would be expected to yield high short-term payoffs. Policy interventions such as farmer education, agricultural extension and land tenure reforms have been suggested in the literature as policy mechanisms for improving farm efficiency[1]; however, how best to improve technical efficiency in the study area remains an empirical issue to be investigated and cannot be fully addressed by this study. On the other hand, if these small farm households are found to be 'poor but (technically) efficient,' à la Schultz (1964), then public investments should be directed toward efforts in shifting the farmers' production possibility frontier. Such efforts could include investments in research and development of new technologies but could also include measures for facilitating adoption of new technologies and improving farmer technical efficiency in utilizing new technologies since development and introduction of new technology may not necessarily lead to their adoption or swift learning in reaching the new frontier achieved through the introduction of new technology.

There is a large literature estimating technical efficiency in farm production in India and elsewhere, which has generally found significant technical inefficiency among farmers (e.g., Kalirajan, 1981 and 1982, also see Battese 1992, for a survey).[2] However, relatively little attention has been paid to the possibility that lack of proper control for subtle differences in environmental factors, including land characteristics, that have the potential to alter findings regarding farm inefficiency—and through this—policy

[1] For example, Singh, et al., (2002, p. 25).
[2] Bagi (1982) and Battese and Coelli (1992), on the other hand, find relatively high technical efficiency of smallholder farms in India.

conclusions regarding the appropriate focus in rural development efforts in the area.[3] Among such potential environmental factors, we focus on the importance of controlling for the effect of microtopography and associated differences in land suitability for agriculture on farm technical efficiency estimates. One of the main findings from our estimates is that small-scale rice farmers in eastern India appear to be considerably more technically efficient in rice production than indicated by farm-level estimates that fail to control for farm plot location on the microtopography.

The rest of the article is organized as follows. Section 2 discusses some of the major characteristics of the poor rice farmers in the study area in eastern India. Section 3 outlines our empirical strategy for testing the sensitivity of the analysis and introduces our empirical model. Section 4 presents estimation results. Section 5 considers policy implications of findings and offers some final observations.

2. Characteristics of the study area and data set[4]

Following the policy reforms of the early 1990s, the Indian economy has displayed renewed dynamism in terms of its growth and achievements in poverty reduction. However, recent research has shown that not all regions of the country have benefited from this improved economic performance and that large variation exists within India in

---

[3] A notable exception is a recent study by Sherlund, et al. (2002), which shows that failure to control for the effect of differences in the environmental characteristics of farm (e.g., climate, pests infestation) can lead to significant overestimation of the degree of technical inefficiency based on analysis of farm survey data from Cote d'Ivoire. Coelli et al. (1999) report similar findings in their analysis of the international airline industry while applying a more general approach.

[4] This section draws heavily on Banik et al. (2004).

terms of the rate of income growth and extent of poverty reduction successes (e. g., Datt and Ravallion, 2002). This follows an earlier post-independence history in the country in which green revolution technologies for wheat and rice cultivation enabled marked increases in agricultural productivity in many agricultural regions of the country in the 1970s and 1980s, but largely bypassed two of the country's extensive agricultural regions: the semi-arid tropics and eastern India's rainfed rice-growing region (Walker and Ryan, 1990). Thanks to the intensive village level studies and longitudinal household surveys carried out by ICRISAT, our knowledge of the former area is substantial. In contrast, the eastern rain-fed rice region has been the subject of relatively little quantitative analysis.

Our study area lies on the Chhotanagpur Plateau, which is part of the so-called 'tribal belt' in eastern India[5]. The data analyzed in this study was collected jointly by the International Rice Research Institute (IRRI) and Indian Statistical Institute (ISI) in the 1998-99 crop season. The survey sample covered two neighboring districts, Giridih and Purulia, in the states of Jharkhand (a part of Bihar state prior to 2000) and West Bengal, respectively. The incidence of poverty among rural households in the area has been estimated to be among the highest in India. Statewide headcount poverty ratios in Bihar and West Bengal were the second and third highest in 1987-88 and second and fifth highest in 1999, respectively (Deaton, 2001). Based on the Planning Commission's official poverty line for 1999, 60% of sampled households were poor according to

[5] The term 'tribal belt' refers to a concentration of districts that run in a band across central India that have high proportions of their populations from Scheduled Tribe backgrounds

income estimates based on our survey data[6] and the average years of schooling of household heads was only 3.6 years.

A total of 541 households were selected for the survey based on a stratified random sample of households in eight villages in each district. In each village, roughly 35 households were randomly selected from Census lists across five landholding groups including landless households. The survey questionnaire captured a host of economic and agricultural characteristics of the households and their farms, but was particularly focused on capturing information on agricultural production activities at the plot level. Our empirical analysis utilizes rice production data from 1,089 plot-level observations (operated by 470 farm households) during the Kharif season (i.e., the monsoon season which generally runs from June to November/December). Table 1 presents sample averages and variances for the key variables used in our production estimates.

Agriculture in the area is largely oriented to rice cultivation for subsistence.[7] Our sample farms are predominantly small farms, and large-scale commercial farms are absent from the area. The maximum size of the farm operated by our sample households was 15 acres (6.1 hectares) and the average farm size was only 2.2 acres (0.9 hectares). This is the result of past land reform efforts that placed limits on the amount of land that could be owned and the division of family landholdings through inheritance across generations. Most sample farms relied on traditional cultivation techniques in their rice

---

[6] This poverty incidence was calculated based on estimates of gross household income, and the figure would likely be much higher if precise estimates of net household income were available.
[7] Only 21% of the sample households reported selling of rice during the survey year.

production. The rate of adoption of modern rice varieties (MVs) was relatively low (see below), and the use of agricultural machinery, such as tractors and power tillers, was nearly nonexistent among sample farms.

One significant feature of the agricultural production environment in the study area is the area's undulating topography in a highly dissected landscape. This characteristic gives rise to low-scale variations in terrain, soil, and water conditions that influence the kinds of crops that can be grown, the time windows for cropping, and feasible cropping systems across plots lying at different levels of the toposequence. Local farmers typically distinguish four different land types according to the land's position on the microtopography: upland, mid-upland, medium land, and lowland. Going from the upland plots to the lowland plots, soil analysis by ISI reveals a trend of increasing soil fertility, consistent with farmers' perceptions of the soil quality along the toposequence. Table 2 summarizes the results of soil analysis from one of the surveyed villages and shows the pattern of increasing chemical nutrients across samples drawn from lower levels of the terrace.[8] Soil nutrient characteristics highlight the importance of relatively small differences in elevation across adjacent plots in defining plot characteristics (e.g., moisture and nutrient holding capacity, vulnerability to erosion).

Farmers have adapted to the local topography by adjusting cropping patterns (particularly rice varieties cultivated) and crop management practices according to plot land type. Upland plots are typically planted with short duration (85-90 days), drought-

[8] At the same time, however, lowlands sometimes suffer from excessive water.

tolerant TVs of rice or traditional minor millets that generally provide low yields. Mid-upland plots are typically planted with medium-duration TVs, while medium land plots—where soil moisture is available for a longer period than on the higher terraces—long-duration TVs of rice are most widely planted. At the bottom of toposequence—on lowland plots—farms typically plant long-duration rice TVs with low inputs of manure or MVs of rice. Planting of traditional varieties predominated, but MV rice is also cultivated (i.e., the share of land area planted with MVs was 21% on lowland and 24% on medium land)—mainly on medium land and lowland plots where the ambient moisture on plots is higher so soils are better suited to MVs which tend to be more sensitive to water availability. Average paddy yields differed significantly across land types, and yields generally increase as one moves down the toposequence. Rice yields averaged 2.1 tons per hectare on upland plots compared to an average yield of 3.3 tons per hectare on lowland plots, according to our survey. Considered together, these characteristics suggest that disaggregating farm technical efficiency estimates across plots of the difference land types and controlling for other low scale (i.e., plot level) differences in environmental conditions can strongly influence estimates of farm technical efficiency.

3. Methodology for testing sensitivity of technical efficiency estimates

We examine the technical efficiency of our sample farmers by estimating stochastic frontier production functions (SFPFs), as pioneered by Aigner et al. (1977, and Meeusen and van den Broeck (1997). In particular, the analysis seeks to evaluate how including details about the microtopographic position affects inferences that can be made regarding small farmer technical efficiency. To do this, we estimate SFPFs at different levels of land aggregation and include different control variables and compare estimation results. SFPF estimation models take the general form:

$$\ln Y_i = f(X_i, Z_i; \beta) + V_i - U_i \, , \tag{1}$$

where $f(.)$ defines the production frontier with i representing i^{th} observation (either plot-level or farm level, as detailed below). Y_i is the total amount (in kilograms) of paddy produced, X_i is a vector of production inputs (land, seed, labor, and fertilizer), Z_i is a vector of additional environmental control variables (i.e., irrigation availability on each plot and village dummy variables capturing institutional/environmental characteristics varying at the village level), and β is the vector of unknown parameters that characterize the production frontier. V_i represents random error (e.g., measurement error) and is assumed to be normally distributed with mean zero and variance σ_v^2. U_i ($\geq$0) captures the non-negative component of the estimation residual and is interpreted as representing technical inefficiency.

It is standard practice in SFPF estimation for the production frontier $f(.)$ to be parameterized as a Translog or Cobb-Douglas functional form. We initially estimate equation (1) as a Translog production frontier taking the form:

$$\ln Y_i = \beta_0 + \sum_{k=1}^{K} \beta_k \ln X_{ki} + ½ \sum_{j=1}^{K} \sum_{k=1}^{K} \beta_{jk} \ln X_{ji} \ln X_{ki} + \sum_{m=1}^{M} \beta_m Z_{mi} + V_i - U_i \, , \tag{2}$$

with $\beta_{jk} = \beta_{kj}$ (k, j = 0, 1, …, K). We test whether Cobb-Douglas is an adequate specification by testing the joint significance of H_0: $\beta_{jk}=0$ for all j, k = 1, …, K. When estimates fail to reject the null hypothesis, we re-estimate the production frontier using a Cobb-Douglas specification.[9]

A variety of distributions have been proposed to characterize the technical inefficiency term U_i in the existing SFPF literature.[10] While distributions that involve two-parameters can accommodate a wider range of possible distributional shapes, using these types of distributions comes at the cost of making parameter identification more difficult (see Ritter and Simar, 1997). Also, the existing literature has not clearly established the empirical significance of using more elaborate specifications of U_i.[11] We initially experimented with alternative distributional assumptions including the exponential, half-normal, and truncated normal, and found that model identification was indeed difficult when the truncated normal distribution was used. The estimated mean of U_i—commonly referred to as parameter μ in the SFPF literature—had large standard errors and was not significantly different from zero. The general pattern of our results did not change across estimates that applied different distributional assumptions for U_i. Consequently, we focus discussion on the results based on the estimates that assumed U_i is distributed as a half-normal distribution (a relatively simple and widely applied

---

[9] The equation estimated in this case takes the form: $lnY_i = \beta_0 + \sum_{k=1}^{K} \beta_k \ln X_{ki} + \sum_{m=1}^{M} \beta_m Z_{mi} + V_i - U_i$

[10] See Kumbhakar and Lovell (2000) for a comprehensive discussion of alternative distributional assumptions found in the literature.

[11] For example, earlier research has shown that while the quantitative magnitudes of predicted firm-level technical efficiency are sensitive to such distributional assumptions, the ranking among observations based on estimated technical efficiency is not (Kumbhakar and Lovell, 2000).

distribution) with variance σ_u^2, which follows recommendations of Ritter and Simar (1997, p. 181), and Kumbhakar and Lovell (2000, p. 90). Adopting one of the more common specifications applied in SFPF estimates has the additional advantage of making it easier to compare our results to earlier studies that used this specification. This will make it easier to assess whether the results of earlier studies estimating production frontiers at the farm level could be biased by their failure to control for plot-level heterogeneity.

We test for technical inefficiency among survey farmers by examining the null hypothesis H_0: $\sigma_u^2=0$ against the alternative hypothesis H_1: $\sigma_u^2>0$. Coelli (1995) shows a one-sided generalized likelihood ratio test statistic is asymptotically distributed as a mixture of chi-square distributions with one degree of freedom. Following Jondrow et al. (1982), and Battese and Coelli (1988), we then predict technical efficiency scores for individual plots (TE_i) as $TE_i = \exp(-U_i)$, conditional on the observed composite error ($V_i - U_i$).

Starting with farm level and moving to plot-level estimates while adding more variables to estimation models to control for the effect of other environmental conditions, we examine how the disaggregation and the addition of environmental variables influence inferences about the extent of farm technical efficiency. Specifically, we estimate production frontiers at three levels of aggregation:

1. Farm level where the output and inputs are aggregated across all plots operated by the household.

2. Plot level analysis where plots of different land types are not distinguished but pooled together, and

3. Individual plot level analysis estimated separately for each land type.

As discussed earlier, farmers typically plant distinct rice varieties on different land types, so we estimate separate production frontiers for each land type. In estimating at each level of the aggregation, we use two model specifications. One specification defines production to depend only upon the level of production inputs (i.e., land area, labor, fertilizer and seed), and the other adds variables to capture the effect of irrigation availability (a dummy variable taking the value one if the plot is irrigated) and the village-level dummy variables. In addition, estimates at the pooled-plot and the plot levels (i.e., for each land type) are carried out separately for plots cultivated with MVs and TVs.

4. Estimation results

The estimated quadratic terms of the Translog production functions are generally statistically significant, so the Translog specification is used in all but one case[12] The quadratic terms were not significantly different from zero in the estimate on medium-land plots so a Cobb-Douglas form was used in this instance.

[12] In addition, all the models were statistically significant (P-value = 0.00) according to the Wald chi-square tests.

4.1. Estimated production frontier parameters

Table 3 summarizes the means and standard deviations of the estimated elasticities of output with respect to the inputs from our production frontier estimates. Estimates show that these elasticities vary significantly across different land types in their pooled and individual plots level estimates, which suggests that the estimated technology parameters that characterize production frontiers are sensitive to the microtopographic position of the farm plot.[13] This is expected since farms plant different rice varieties and apply different inputs on plots of different land types, and is consistent with the general conclusions of Sherlund et al. (2002). Elasticities also varied—although less consistently—with the inclusion of additional control variables (i.e., irrigation availability and village dummy variables).[14]

4.2. Technical efficiency estimates

Table 4 summarizes the results of technical efficiency estimates, reporting the statistical significance and predicted technical efficiency scores under the various model specifications. Results generally show that technical efficiency estimates carried out at the farm level differ significantly from estimates made at more disaggregated levels (i.e.,

[13] While the relatively small (and occasionally negative) elasticity of labor is somewhat puzzling, it is consistent with previous findings from rice farmers in Bangladesh (Sharif and Dar, 1996) and wheat farmers in Pakistan (Battese and Broca, 1997). A plausible explanation for the negative coefficients estimated for labor input in some of the specifications is that labor input is pre-determined to a much lesser extent than other inputs (i.e., decisions regarding the size of plot to cultivate and the amount of seed to apply must be made at the start of the planting season) and increased application of labor is a common response to crop management problems (e.g., drought, or weed/insect infestations).

[14] Coefficient estimates are not reported due to space constraints, but are available from the corresponding author.

farm production across land types and plots). Our estimates indicate that there is significant technical inefficiency among the rice farms at the household aggregate level—a result that is consistent with earlier studies. As shown in the first column of Table 4, the null hypothesis that there is no technical inefficiency (i.e., σ_u equals zero) is strongly rejected (probability value of less than 0.01 in farm-wide estimates). Average technical efficiency scores are 0.75 (for the specifications with production inputs only) and 0.8 (for specifications with additional irrigation and village heterogeneity controls). Estimated technical efficiency scores are roughly comparable to those found in the earlier estimates base on data from developing country settings (Battese, 1992).[15] The analysis at the aggregate farm level suggests that irrigation availability and variables capturing village-level heterogeneity have relatively little effect on farm technical efficiency, a result which sharply contrasts that of Sherlund et al. (2002).

Estimates of farm technical efficiency made at the more disaggregated plot-level yields results that change the inferences that can be drawn regarding farm technical efficiency, providing a more complex pattern of results. Plots planted with MVs are shown to be efficient (i.e., estimates fail to reject the null hypothesis of no technical inefficiency) and point estimates of the ratio of standard deviations λ—σ_u/σ_v : an indicator of the relative contributions of *u* and *v* to the composite error term—are close to zero (See column two on Table 4), and the average predicted value of technical efficiency is close to one. The finding that rice cultivation using MVs among sampled farms in

[15] Caution is warranted in interpreting these results, however, because comparisons of efficiency scores say nothing about relative efficiency *across* samples of farmers (Coelli et al., 1998, p. 247).

eastern India is operating near the production frontier sharply contrasts with results of earlier studies. Kalirajan (1982) and Sharif and Dar (1996) found significant inefficiency among rice farms planting MVs, however, these earlier studies relied on data from subsistence oriented rice farms covering different years and geographical areas than our study.[16] Another possible explanation for the different results is that farm technical inefficiency in the early stage of MV introduction has been overcome as farmers have learned and adapted standard practices over the years following MV introduction.

While farms cultivating rice plots planted with MVs are found to be technically efficient, the equivalent estimates show plots planted with TVs display significant technical inefficiency. The mean predicted technical efficiency scores range from 0.75 to 0.79, as shown in the third column of Table 4. However, when estimates are carried out separately for plots of each land type, estimates find statistically significant technical inefficiency estimates for medium land and lowland plots, but not for upland or mid-upland plots. The model with controls for the availability of irrigation on the plot and village effects gives point estimates of λ at 2.5 on lowland plots and 3.4 on medium land plots, which suggests that the technical inefficiency term (U_i) dominates the composite error term (V_i-U_i).

In the case of upland and mid-upland plots, the null hypothesis of no technical efficiency is rejected in the basic model (i.e., without irrigation and village-level dummy

[16] The data used in these studies came from Tamil Nadu State in the late 1970s and Bangladesh in the mid-1980s, respectively.

variables). Once irrigation and village dummy variables are introduced, however, the null hypothesis is no longer rejected, and the point estimates of λ become very small (less than 0.1). Accordingly, adding indicators of irrigation and village level heterogeneity thus significantly influences inferences regarding the technical efficiency of rice cultivation on upland and mid-upland plots planted with TVs.[17] In contrast, adding environmental controls does not significantly influence inferences regarding technical efficiency on medium land and lowland TV plots.

To summarize, we find that technical inefficiency is prevalent among the more fertile plots lying in the lower portions along toposequence (i.e., medium-land and lowland plots) while systematic technical inefficiency is not present on plots in less favorable upper portions of the terrace toposequence (upland and mid-upland plots). Our estimates for plots planted with modern rice varieties (cultivated mainly on medium land and lowland posts) also failed to find systematic technical inefficiency across surveyed smallholder farms.

A likely explanation for the more complex picture that emerges from plot-level estimates—in which smallholder farms display efficiency in cultivating TVs on middle and upper terrace plots but inefficiency on medium-land and lowland plots— is that this results from the more heterogeneous and uncertain agricultural conditions encountered on higher terraces. The water holding capacity and soil nutrient composition of upland and mid-upland plots appear to be relatively more heterogeneous than those of the lower

[17] This finding is in line with that of Sherlund et al. (2002).

terraces. In addition, the tendency for nutrients to be carried off plots on higher portions of the toposequence—particularly during heavy monsoon rains—and to be transferred to lower terraces, a process that is beyond farmers' control, is likely to depend upon idiosyncratic characteristics of the local topography, and increase the homogeneity of medium land and lowland plots relative to upper terraces. As a result, the amount of production farms can garner from rice cultivated on upland and mid-upland plots tends to be more uncertain and appears to depend to a greater extent on stochastic environmental outcomes than is the case for output levels from lower terrace plots. This is suggested by the relatively small λ (i.e., the random error component dominating the composite error term) in our upland and mid-upland plot estimates. In contrast, the relatively more homogeneous and more stable water-holding capacity and nutrient characteristics of soils on lower portions of the toposequence appear to enable farm cultivation practices and management skills—rather than random factors—to determine yields on lower terrace plots. The relatively larger estimates of λ obtained on estimates for lowland and middle land plots are consistent with such an explanation. Since we are estimating separate production frontiers for each land type, the levels of production frontiers are lower (i.e., yields are lower) for upper terraces than for lower terraces, but the distance of individual farms from the frontier tends to be dominated by stochastic soil conditions largely beyond farmers' control. As a result, rice plots on upper terraces appear to be operating more or less with the same level of technical efficiency (i.e., absence of significant technical inefficiency).

A practical implication of these findings is that it will likely be difficult to increase productivity on less favorable upper terraces without shifting the production frontier, while results also suggest there is potential to improve the technical efficiency of some farmers in rice cultivation on lower terrace plots. Methodologically, these results indicate that aggregation of production inputs and outputs across individual plots to farm-wide totals in SFPF estimates yields estimates that cause farms to appear considerably less technically efficient than they actually are once explicit account is taken of the production effects of microtopography, irrigation availability, and village level characteristics by including these variables in plot level estimates.

4.3. Are MV-adopters systematically more efficient than non-adopters?

Because one might expect farms that are technically proficient in MV cultivation on medium-land and lowland plots (68% of the MV plots in our survey were on plots of these two land types) to be efficient in the production of all rice varieties on these plots, the finding that there is significant technical inefficiency on lower-terrace plots planted with TVs merits additional investigation. One potential explanation is that more technically efficient farms adopted MVs while farms that are less technically efficient were less likely to adopt MVs. In other words, unobserved farmer characteristics correlated with greater efficiency may also be correlated with MV adoption. Alternatively, this could result if the same farmers found to be technically efficient in MV cultivation on some lower terrace plots are in fact less technically efficient in cultivating TVs on other lower terrace plots. Farms typically cultivate rice on plots of more than one land type, and a substantial number of plots operated by 'MV adopters' (defined here as those who cultivate MV on at least one plot) are planted with TVs. Only 9% of the MV-adopters planted MVs on all of their farm's plots (91% cultivated MVs on some plots and TVs on others).

We explore whether MV adopters are technically more efficient than non-adopters in their cultivation of TVs on lower terrace plots in two ways. First, we examine whether the predicted technical efficiency scores (TE_i) for TV cultivation are significantly different between the MV-adopter and non-adopter groups according to our SFPF estimates (from the full model) reported in Table 4. Second, we examine whether being an MV adopter has a significantly negative association with technical inefficiency scores by re-estimating the same SFPF for each land type as reported in Table 4 except that we now specify the variance of the technical efficiency term U_i to be a function of an 'MV adopter dummy' (a dummy variable taking value one if the farm operator has at least one plot planted with MVs).

As reported in Table 4 (in the last two rows), the average technical efficiency scores are similar across MV adopters and non-adopters. Scores are slightly higher among MV-adopters on medium land plots (and when plots of all land types are pooled), but the pattern is reversed on lowland plots. Accordingly, our estimates provide weak evidence of higher technical efficiency among MV adopters on medium land plots, but estimates do not display a consistent efficiency gap between the MV-adopters and the non-adopters in TV cultivation.

Our second approach to examine whether there are systematic differences in technical efficiency between MV-adopters and non-adopters is to introduce an MV-adopter dummy as a covariate in the determinants of technical inefficiency term (U_i); we assume that $\sigma^2_{ui} = \exp(\boldsymbol{\gamma}'\boldsymbol{Z}_i)$, where the $\boldsymbol{Z}_\mathrm{i}$ vector consists of an intercept and the MV adopter dummy. These estimates reveal that the coefficient on the MV adopter dummy is not significantly different from zero in any of the specifications[18], so provide further evidence in support of the conjecture that MV-adopters are not any more technically efficient than non-adopters in their cultivation of TVs on lower terraces. Had MV-adopters been found to be more technically proficient in TV cultivation on medium-land and lowland plots, it would have supported the hypothesis that unobserved farmer heterogeneity such as technical know-how and motivation explained the different levels of technical efficiency on MV plots and the TV plots on lower terraces. To summarize, our results suggest that surveyed farms exhibit varying levels of technical proficiency across plots of different land-types planted with TVs, and across plots of the same land types (i.e., medium land and lowland) planted with MVs and TVs and that this does not appear to be explained by selection bias.

4.4. MV vs. TV cultivation on lower terraces

If selection bias cannot explain the somewhat paradoxical finding that the same farms displayed different degrees of technical efficiency between lower terrace plots

[18] These estimation results are not reported here in order to conserve space, but are available from the authors upon request.

cultivated with MVs and TVs, then what can explain this result? While answering this question fully with cross-sectional data is difficult,[19] we can offer a few possible explanations. One possibility is that, by the late 1990s, MV rice cultivation technology had become well understood and homogeneously applied by adopting farms while the TV farming technology remained more idiosyncratic and continued to depend significantly on farm experience. As we see below, we find evidence that accumulated farm experience (proxied by the age of the household head) positively affects technical efficiency in TV cultivation, suggesting that learning from experiences plays an important role in raising farm efficiency in TV cultivation.

In addition, literature from agronomy (as well as technicalities involved in SFPF estimation) offer additional explanations for the different levels of technical efficiency observed for cultivation of MVs and TVs on lower terraces. As noted earlier, water availability on lower terrace plots is generally more favorable than on upper terrace plots, but due to the paucity of water management infrastructure in the study area it still fluctuates with rainfall.[20] The greater sensitivity of MV yields to water availability means that yields from cultivation of TVs on lower terrace plots are more certain than yields from MV cultivation.[21] Accordingly, the level of production from MVs cultivated on medium and lowland plots likely depends more on stochastic environmental outcomes

[19] Construction of a panel dataset is currently underway, and with such data we will be able to investigate both the farms' decision to adopt MVs and their technical efficiency at the plot-level with statistical control of the effects of unobserved plot-level heterogeneity.
[20] In the case of lowland, excess water, as well as the shortage of water, can be a problem depending on the fluctuations in the water table level.
[21] This characteristic of rice cultivation in the study area is detailed in Maiti and Bagchi (1993).

(rather than farm efficiency) than production outcomes from TV cultivation. Our SFPF estimates showed estimated standard deviations of the random error terms (i.e., σ_v) for the plots planted with MVs average roughly 0.3 compared with estimates in the range of 0.1 to 0.2 for medium-land and lowland plots cultivated with TVs. The greater variance in yields for plots cultivated with MVs makes the estimated λ small relative to λ estimated for plots cultivated with TVs (see Table 4). This explanation somewhat parallels that offered earlier in the paper to explain the different efficiency levels observed in TV cultivation on upper and lower terrace plots.

4.5. Why are the MV adoption rates so low?

While these offer possible explanations for the difference in the estimated technical efficiency between lower terrace plots cultivated with MVs and TVs, questions remain concerning: (1) the low rate of MV adoption, and (2) the possible sources of the technical inefficiency found for lower terrace TV crops. Again, fully addressing these questions would require richer data than is currently available. Nonetheless, we offer some preliminary conjectures loosely supported by evidence from the cross-sectional data.

It is puzzling that the MV adoption rate remains low so many years after MVs were first introduced. Difficulty with learning proper techniques for cultivating MVs would not appear to offer a viable explanation since farms that have adopted MV appear to be operating near the production frontier. One possible explanation is that severe cash constraints among surveyed farm households force credit rationing and greater reliance on non-purchased agricultural inputs. Modern inputs required for MV cultivation (e.g., chemical fertilizer) are typically financed with cash income from non-farm sources since credit markets appear to be extremely limited in the study area.[22] Our survey data indicate, for example, that the average non-agricultural income of households adopting MVs is twice that of non-adopting households (Rupees (Rs.) 3,800 compared to Rs. 1,800), which is consistent with MVs adoption being constrained by the lack of opportunities to earn cash (and the poorly developed market for agricultural credit) to finance the purchase of modern inputs required for MV cultivation. In addition, given the high level of poverty in the area, and the relatively high sensitivity of yields to water availability, the low level of MV adoption and cultivation of MVs on only a portion of farm land by adopters can be understood as a risk mitigating strategy.

Another possibility is that the MVs currently available in the study area are poorly suited to the environmental conditions of the East Indian plateau, and only the most favorable lower terrace plots–on which water management is possible–are favorable to MV cultivation. Unfortunately, small variations in land quality across lowland plots cannot be directly observed in our dataset. However, if this were the case, then either technical innovation to develop (and introduce) new drought tolerant MVs or investments in infrastructure to better manage water on farm plots would be necessary to enable study area farms to adopt high yielding rice varieties on a larger scale.

4.6. Potential sources of technical inefficiency in TV cultivation

[22] The lack of agricultural credit is found in the results of the survey carried out for this study and has been documented in Ramachandran and Swaminathan (2001).

Returning to the second question of why is it that some farmers are technically more efficient than others in TV cultivation on lower terrace plots: We explore this question by re-estimating stochastic frontiers with the added assumption that the variance of the technical inefficiency term U_i is a function of a set of potential determinants of inefficiency (i.e., $\sigma_{ui}^2 = \exp(\boldsymbol{\gamma}'\boldsymbol{Z}_i)$). The list of potential determinants of technical inefficiency ($\boldsymbol{Z}_i$) measured in our dataset is rather limited, however, largely consisting of household-level—rather than plot-level—variables (e.g., years of schooling of the household member with highest educational attainment, age of the household head as a proxy for farming experience, farm distance from local markets as indicated by travel time to the nearest local market, total land area operated by the household, and the share farm landholding of each land type).

The results of this analysis are summarized in Table 5.[23] We find that greater distance from markets has a positive and statistically significant effect on technical inefficiency under all estimation model specifications. If distance was negatively correlated with ease in acquiring information on new agricultural techniques (for example, if greater distance was associated with fewer visits from agricultural extension agents or commercial traders who transmit information on new technologies), then relatively remote farms would be expected to display lower technical efficiency. Distance from markets also increases transactions costs in purchasing agricultural inputs (such as fertilizer) and technically inefficient use of inputs could result from the relative over-

[23] Estimated production frontier parameters are not reported here in order to conserve space, but are available from the corresponding author upon request.

reliance on non-market inputs such as family labor, farm manure, and seed stored from prior year's harvest due to the higher transaction costs, and thus explain the positive relationship between farm distance from markets and technical inefficiency.

Farm household educational attainment has a significant positive association with technical efficiency.[24] Greater schooling could potentially enhance farm technical efficiency either through acquisition of knowledge relevant to agriculture (taught directly at school or through outside sources such as reading newspaper, which is made possible by literacy education) or through enhancing household capacity to learn from farming experiences. Following Rosenzweig (1995), we can use a target-input model to examine the empirical relationship between schooling and farm productivity (in particular, whether schooling and experience are substitutes or compliments) by including an interaction term between schooling and experience as a determinant of the technical inefficiency term. As shown in Table 5 (column 4), the estimation coefficient on the interaction term suggests that schooling and experiences are substitutes rather than complements on medium-land (but not lowland) plots. This can be interpreted to suggest that schooling increases acquisition of new information but does not enhance the efficiency of learning from experience, and that the returns to schooling tend to decline as households accumulate experience.[25]

We also find that farms operating on lands with a higher proportion of lower

[24] Initially we also have used the schooling of the household head instead of the maximum schooling, but it was not significant. So it is the maximum education rather than the head's education that appears to matter.
[25] See Rosenzweig (1995) for the logic behind this interpretation of the interaction term.

terrace plots are more technically efficient in some estimates—although the level of statistical significance is lower—,and that farm size does not have a statistically significant effect on farm technical efficiency. Considered together, this analysis provides some additional evidence that the distinct characteristics of plots influence farming outcomes. However, without stronger data (e.g., panel data or additional variables measured at the plot rather than the household level), we are unable to rule out the possibility that yet unobserved heterogeneity across plots of a given land type might be driving some of our results.

5. Policy implications

A number of policy implications can be drawn from these findings. One key finding concerns the importance of low scale differences in topography in driving land use and production outcomes in our study area. Efficiency estimates carried out at the farm level suggest farms are technically inefficient, but more disaggregated estimates reveal a more complex picture of farm technical capacity—with farms displaying technical efficiency on plots of certain land types planted with TVs and plots of other land types planted with MVs. The contrasting results in technical efficiency estimates between the upper and the lower terraces (as well as between the MV- and TV-planted plots) suggest that distinct policy interventions for increasing productivity of different land types are likely to be called for. For upland and mid-upland, there seems to be relatively little room for improving technical efficiency under the current technology, and existing MVs are unlikely to be widely adopted due to unfavorable soil moisture conditions on these lands. Development and introduction of new technology—particularly new rice varieties with higher tolerance to water stress (instead of improving technical efficiency based on the existing technology) is suggested for raising productivity in those land situations.

Our finding that MV adoption levels remain low in the survey area despite the fact that MV adopters display technical proficiency in MV cultivation suggests addressing the constraints that prevent many poor farm households from adopting MV should be high on research and policy agendas in eastern India. There are at least two possible explanations for the low rate of adoption among surveyed farms: 1) that farms are cash (credit) constrained; and 2) that land in the area that is well suited to cultivation of the currently available MVs is scarce. Appropriate policy interventions would depend on which of these is true, but further study is needed to determine this as the present research is unable to distinguish these alternative explanations. If local agricultural conditions constrain adoption, then development of new high yielding varieties with improved drought adoption tolerance may be desirable, and development and introduction of low cost water control technologies would hold promise of improving the MV adoption rate. Alternatively, if the low rate of MV results from binding cash/credit constraints, then policy interventions addressing this aspect of market imperfection would be needed.

Our research also suggests there is potential for improving technical efficiency in TV cultivation on the medium land and lowland (e.g., technical extension to enable inefficient farms to produce closer to the production frontier). Development and diffusion of sound crop management practices for rainfed TVs through agricultural research could also be promising for these plots. Our analysis also suggests that investing in infrastructure could reduce the gap in technical efficiency levels between remote areas and more accessible areas, as could improved access to schooling. However, given our findings that the observed technical inefficiency is not as extensive as it might first appear from more aggregate analysis, efforts at improvement of technical efficiency may have relatively limited impact in terms of improving farm productivity and food security in Eastern India.

6. Conclusions

Existing studies applying stochastic frontier production function estimation to examine technical efficiency of farms in the context of developing country agriculture have found widespread evidence of farm inefficiency. In contrast, we find that farm technical efficiency varies across farm plots distinguished by their position in a low-scale toposequence and by the rice variety (modern or traditional) cultivated. Analysis of farm technical efficiency at the disaggregated plot-level suggests that poor rice farming households in eastern India are considerably more technically efficient than they appear based on the aggregate farm-level analysis. Farms appear to be efficient in the cultivation of some plots and inefficient in others—rather than being uniformly inefficient in farming. To understand why this is the case, analysis must consider the local environment and distinct cultivation practices applied in cultivation of rice on plots of different land types. Farm-wide analysis incorrectly attributes differences in output levels to farm mismanagement when more disaggregated analysis indicates technical shortcomings are due to small scale variations in soil quality and other environmental characteristics observable only at the plot level.

Acknowledgments

Nobuhiko Fuwa was on the staff of the International Rice Research Institute (IRRI), which funded this project, when the initial version of this paper was written. The authors would like to acknowledge the support and many inputs received from Mahabub Hossain and Suan Pheng Kam. We are also grateful to Lorena Villano who provided superb research assistance. The authors would like also to thank Seiro Ito, Kensuke Kubo, Takashi Kurosaki, Yasuyuki Sawada, the participants in the American Agricultural Economics Association annual meetings in Providence in July 2005 and the two anonymous referees for helpful comments.

References

Aigner, D. J., C. A. K. Lovell, and P. Schmidt. 1977. “Formulation and estimation of stochastic frontier production models.” Journal of Econometrics 6: 21-37.

Bagi, F.S. 1982. “Economic efficiency of sharecropping: reply and some further results.” Malaysia Economic Review 27:86-95.

Banik, P, C. Edmonds, N. Fuwa, S.P. Kam, L. Villano, and D.K. Bagchi. 2004. Natural Resource Endowments, Subsistence Agriculture, and Poverty in the Chhotanagpur Plateau. International Rice Research Institute Discussion Paper Series No. 47. Los Baños, Laguna, Philippines.

Battese, G. 1992. "Frontier production functions and technical efficiency: a survey of empirical applications in agricultural economics." Agricultural Economics 7:185-208.

Battese, G. and T. Coelli. 1988. "Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data." Journal of Econometrics 28: 387-399.

Battese, G., and T. Coelli. 1992. "Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India." Journal of Productivity Analysis 3: 153-169.

Battese, G. and S. Broca. 1997. "Functional forms of stochastic frontier production functions and models for technical inefficiency effects: a comparative study for wheat farmers in Pakistan." Journal of Productivity Analysis 8: 395-414.

Coelli, T. 1995. "Estimators and Hypothesis Tests for a Stochastic Frontier Function: A Monte Carlo Analysis." Journal of Productivity Analysis 6: 247-268.

Coelli, T., S. Perelman, and E. Romano. 1999. "Accounting for environmental influences in stochastic frontier models: with application to international airlines." Journal of Productivity Analysis 11: 251-273.

Coelli, T., D.S.P. Rao, and G.Battese. 1998. An Introduction to Efficiency and Productivity Analysis. Boston: Kluwer Academic Publishers.

Datt, G. and M. Ravallion. 2002. "Is India's Economic Growth Leaving the Poor Behind?" Journal of Economic Perspectives 16(3): 89-108.

Deaton, A. 2001. "Computing prices and poverty rates in India 1999-2000." Working Paper Research Program in Development Studies. Princeton: Princeton University.

Jondrow, J., C.A.K. Lovell, I.S. Materov, and P. Schmidt. 1982. "On the estimation of technical inefficiency in the stochastic frontier production function model." Journal of Econometrics 19: 233-238.

Kalirajan, K. 1981. "An econometric analysis of yield variability in paddy production." Canadian Journal of Agricultural Economics 29: 283-294

__________. 1982. "On measuring yield potential of the high yielding varieties technology at farm level." Journal of Agricultural Economics 33: 227-236.

Kumbhakar, S. and C.A.K. Lovell. 2000. Stochastic Frontier Analysis. New York: Cambridge University Press.

Maiti, A.K. and D.K. Bagchi. 1993. Perception, performance and potential of development in Usri watershed area of Bihar plateau region: An eco-systemic approach. Project Report Submitted to ICSSR, New Delhi, pp. 123.

Meeusen, W., and J. van den Broeck. 1977. “Efficiency estimation from Cobb-Douglas production functions with composed error.” International Economic Review 18: 435-444.

Ramachandran, V.K., and M. Swaminathan. 2001. “Does Informal Credit Provide Security? Rural Banking Policy in India.” Geneva: International Labor Office, pp. 28.

Ritter, C., and L. Simar. 1997. “Pitfalls of Normal-Gamma Stochastic Frontier Models.” Journal of Productivity Analysis 8: 167-182.

Rosenzweig, Mark. 1995. “Why Are There Returns to Schooling?” American Economic Review Papers and Proceedings 85. 153-158.

Schultz, T.W. 1964. Transforming Traditional Agriculture. New Haven: Yale Univ. Press.

Sharif, N. R. and A.A. Dar. 1996. “An Empirical Study of the Patterns and Sources of Technical Inefficiency in Traditional and HYV Rice Cultivation in Bangladesh.” Journal of Development Studies 32: 612-629.

Singh, R.B., P. Kumar, and T. Woodhead. 2002. “Smallholder Farmers in India: Food Security and Agricultural Policy.” Publication 2002/03. Bangkok, Thailand: Regional Office for Asia and the Pacific, Food and Agriculture Organization.

Sherlund, S.M., C.B. Barrett, and A.A. Adesina. 2002. “Smallholder technical efficiency controlling for environmental production conditions.” Journal of Development Economics 69: 85-101.

Walker, T. S. and Ryan, J. G. 1990. Village and Household Economies in India’s. Semi-arid Tropics. Baltimore: Johns Hopkins University Press.

Table 1. Summary statistics for variables used in SFPF estimates

Sample/Sub-Sample (sample size) Variable	Sample mean	Coefficient of variation	Minimum value	Maximum value
All Kharif season rice plots planted with modern varieties (N=169)				
production (kg.)	1,044.300	6.179	45.000	8,420.00
land (acre)	0.892	0.005	00.050	12.160
seed (kg.)	42.500	0.251	02.000	550.00
fertilizer (100 kg.)	2.803	0.017	00.000	19.800
labor (person-days)	65.780	0.389	06.000	368.00
upland land-type plot (0/1)	0.036	--	00.000	1.00
mid-upland plot (0/1)	0.284	--	00.000	1.00
medium land plot (0/1)	0.254	--	00.000	1.00
lowland plot (0/1)	0.426	--	00.000	1.00
irrigation available (0/1)	0.090	--	00.000	1.00
All Kharif season rice plots planted with traditional varieties (N=920*)				
production (kg.)	907.600	1.174	30.000	12,592.00
land (acre)	0.940	1.055	0.0250	10.47
seed (kg.)	48.619	1.131	1.000	525.00
fertilizer (kg.)	2.260	1.343	0.000	36.00
labor (person-days)	74.484	0.986	3.000	823.00
upland land-type plot (0/1)	0.114	--	0.000	1.00
mid-upland plot (0/1)	0.485	--	0.000	1.00
medium land plot (0/1)	0.140	--	0.000	1.00
lowland plot (0/1)	0.260	--	0.000	1.00
irrigation available (0/1)	0.090	--	0.000	1.00
Kharif season traditional variety rice plots on upland (N=105)				
production (kg.)	471.300	4.489	40.000	1,645.000
land (acre)	0.726	0.007	0.030	4.000
seed (kg.)	36.340	0.346	2.000	140.000
fertilizer (kg.)	0.966	0.009	0.000	8.680
labor (person-days)	47.380	0.451	3.00	267.000
irrigation available (0/1)	0.048	--	0 .0000	1.000
Kharif season traditional variety rice plots on middle upland (N=446)				
production (kg.)	848.000	1.901	30.000	7,350.000
land (acre)	0.972	0.002	0.025	9.000
seed (kg.)	50.128	0.112	1.000	420.000
fertilizer (kg.)	2.350	0.005	0.000	36.000
labor (person-days)	77.910	0.175	03.50	823.000
irrigation available (0/1)	0.100	--	00.00	1.000
Kharif season traditional variety rice plots on medium land (N=129)				
production (kg.)	1,019.500	7.903	90.000	7,140.000
land (acre)	0.928	0.007	0.060	6.000
seed (kg.)	46.257	0.359	2.750	525.000
fertilizer (kg.)	2.473	0.019	0.000	27.000
labor (person-days)	77.054	0.597	6.000	430.000
irrigation available (0/1)	0.147	--	0.00	1.000
Kharif season traditional variety rice plots on lowland (N=239)				
production (kg.)	1,148.900	1.263	35.000	12,592.000
land (acre)	0.977	1.162	0.030	10.470
seed (kg.)	52.335	1.138	2.000	490.000
fertilizer (kg.)	2.546	1.223	0.000	20.000
labor (person-days)	78.192	0.961	3.500	498.000
irrigation available (0/1)	0.059	--	0.00	1.00

*While the total number of plot-level observations with TV cultivation is 920, information on land type is missing in one observation. Thus the total plot-level observations *with known land types* are 919 (=105+446+129+239).

Table 2. Composition of nutrients across land types defined by position on the toposequence

Land type	Number of samples	Org. C (%)	Ave. P (kg./ha)	Ave. K (kg./ha)	Total N (%)
Upland	3	0.38	12	84	0.03
Mid-upland	6	0.53	18	82	0.05
Medium land	6	0.56	21	267	0.05
Lowland	21	0.77	24	185	0.07

Notes: C-Carbon, P-Potassium, K-Phosphorous, and N-Nitrogen.

Source: Soil chemical analysis conducted at Indian Statistical Institute, Kolkata, India.

Table 3. Input elasticities and standard deviations from SFPF estimates

	Alternative plot/land-type disaggregation levels						
		All plots pooled:		Land-type specific estimates:			
Production input	Farm level	Modern varieties (MV) only	Traditional varieties (TV) only	upland (TV only)	mid-upland (TV only)	medium land (TV only)	lowland (TV only)
(A) Minimum production function model with production inputs only:							
Land	0.7088	0.4728	0.5787	0.2195	0.5782	0.8690	0.6363
	(0.134)	(0.211)	(0.183)	(0.260)	(0.170)	(0.046)	(0.156)
Fertilizer	0.0436	0.0646	0.0565	0.0749	0.0648	0.0069	0.0160
	(0.025)	(0.054)	(0.032)	(0.174)	(0.046)	(0.012)	(0.034)
Labor	-0.0521	0.0155	0.0702	0.1182	0.0379	-0.0092	0.0889
	(0.042)	(0.114)	(0.100)	(0.182)	(0.075)	(0.042)	(0.094)
Seed	0.2646	0.3703	0.2580	0.4075	0.2726	0.0841	0.2320
	(0.095)	(0.065)	(0.105)	(0.228)	(0.178)	(0.035)	(0.143)
(B) Full production function model with irrigation and village dummies:							
Land	0.617	0.4374	0.5219	0.3067	0.4758	0.8556	0.5785
	(0.128)	(0.238)	(0.189)	(0.256)	(0.147)	(0.041)	(0.158)
Fertilizer	0.0354	0.0301	0.0511	0.0947	0.0630	0.0083	0.004
	(0.026)	(0.036)	(0.037)	(0.117)	(0.0447)	(0.011)	(0.032)
Labor	-0.0358	-0.0524	0.0482	0.1287	0.0349	0.00259	0.0743
	(0.042)	(0.115)	(0.088)	(0.157)	(0.0823)	(0.043)	(0.102)
Seed	0.3367	0.4771	0.3280	0.3594	0.3766	0.0631	0.3278
	(0.113)	(0.120)	(0.127)	(0.161)	(0.170)	(0.027)	(0.112)

Table 4. Estimates of farm technical efficiency in rice cultivation

Mixture Wald chi-square test statistics (h_0: σ_u=0) for the presence of technical inefficiency (p-value in parentheses) and estimated $\lambda = \sigma_u / \sigma_v$

	Alternative plot/land-type disaggregation levels						
		All plots pooled:		Land-type specific estimates:			
	Farm-wide (household) level	Modern varieties (MV) only	Traditional varieties (TV) only	upland (TV only)	mid-upland (TV only)	medium land (TV only)	lowland (TV only)
sample size	470	169	920 [a]	105	446	129	239
functional form	Translog	Translog	Translog	Translog	Translog	Cobb-Douglas	Translog
(A) Minimum production function model with production inputs only:							
test statistic (p-value)	21.24 (0.00)	0.00 (1.00)	13.58 (0.00)	4.93 (0.013)	4.06 (0.022)	3.68 (0.027)	17.76 (0.00)
estimated $\lambda = \sigma_u / \sigma_v$	λ=1.900	λ=0.0158	λ=1.402	λ=2.383	λ=1.149	λ=1.373	λ=2.3601
Mean technical efficiency score (all farms)	0.749 [470][a]	0.9955 [169][a]	0.7531 [920][a]	0.7015 [105][a]	0.8010 [446][a]	0.8255 [129][a]	0.7196 [239][a]
(B) Full production function model with irrigation and village dummies:							
test statistic (p-value)	9.03 (0.001)	0.00* (1.00)	9.14 (0.001)	0.00 (1.00)	0.00 (1.00)	12.79 (0.00)	10.59 (0.001)
estimated $\lambda = \sigma_u / \sigma_v$	λ=1.458	λ=0.0238	λ=1.2716	λ=0.0401	λ=0.0150	λ=3.391	λ=2.501
Mean technical efficiency score (all farms)	0.798 [470][b]	0.9940 [169][b]	0.7877 [920][b]	0.9898 [105][b]	0.9965 [446][b]	0.7860 [129][b]	0.7240 [239][b]
(MV adopters Only [c]) 0.8176 [128][b]	0.9940 [169][b] 0.792 [171][b]	0.990 [20][b] 0.996 [99][b]	0.813 [19][b] 0.705 [33][b]				
(non adopters only [d])	0.7909 [342][b]	NA	0.787 [749][b]	0.990 [85][b]	0.996 [347][b]	0.781 [110][b]	0.727 [206][b]

Notes: [*]The model also include dummy variables for each land type. [a] While the total number of plot-level observations with TV cultivation is 920, information on land type is missing in one observation. Thus the total plot-level observations *with known land types* are 919 (=105+446+129+239). [b] Number of observations in square bracket. [c] MV adopters = Farmers with at least one plot planted with modern rice varieties (MVs). [d] Non-adopters = Farmers who do not plant MVs on any plot.

. **Table 5. Determinants of technical inefficiency**+ [$U_i \sim N^+(0, \sigma_u)$; $\sigma_{ui}^2 = \exp(Z_i\delta)$]

	Medium land				Lowland			
Z variables:	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Highest educational attainment in household	-0.074 * (1.72)	-0.068 * (1.65)	-0.083 ** (2.12)	-0.336 ** (2.31)	-0.047 * (1.74)	-0.43 (1.51)	-0.057 ** (2.09)	0.081 (0.86)
Distance to nearest market	0.049 ** (3.25)	0.046 ** (3.45)	0.042 ** (3.42)	0.007 ** (2.05)	0.025 ** (2.06)	0.026 ** (2.04)	0.022 ** (1.97)	0.010 ** (2.08)
Age: head of household (HH)	-0.022 ** (1.96)	-0.020 * (1.92)		-0.057 ** (2.52)	-0.009 (1.04)			0.013 (0.87)
Highest educat. x Age of HH				0.005 * (1.98)				-0.003 (1.53)
Size of land holding	0.855 (1.53)				0.359 (1.45)			
% land in mid-uplands	-0.912 (1.59)	-0.078 (0.48)			-0.210 (0.70)	0.171 (1.11)		
% land in medium lands	-1.147 * (1.90)	-0.292 (1.44)			-1.038 ** (2.01)	-0.830 (1.54)		
% of in lowlands	-0.799 (1.34)	0.080 (0.48)			-0.618 ** (2.19)		-0.283 * (1.71)	

+Estimated production frontier parameters are not reported here in order to conserve space, but are available from the authors upon request.
** Statistically significant at 5% level.
* Statistically significant at 10% level.