Exogenous Production Shocks and Technical Efficiency Among Traditional Ivorien Rice Farmers

Shane M. Sherlund and Christopher B. Barrett

May 1998

Prepared for presentation to the American Agricultural Economics Association 1998 Annual Meeting

The authors are graduate student and associate professor, respectively, in the Department of Economics, Utah State University, Logan, UT 84322-3530. From August 1998, our affiliations will be different. Sherlund will be a graduate student, Department of Economics, University of Wisconsin-Madison, Madison, WI 53706, and Barrett will be an associate professor, Department of Agricultural, Resource, and Managerial Economics, Warren Hall, Cornell University, Ithaca, NY 14853. We thank the West Africa Rice Development Association for making the data available, and David Aadland, Akin Adesina, Tim Dalton, and Quinn Weninger for helpful discussions. The usual disclaimer applies. This work was supported by the Utah Agricultural Experiment Station and approved as journal paper UAES ####.

Exogenous Production Shocks and Technical Efficiency Among Traditional Ivorien Rice Farmers

By Shane M. Sherlund and Christopher B. Barrett

Abstract

This paper uses a unique panel data set and data envelopment analysis (DEA) techniques to obtain estimates of technical efficiency for 492 traditional rice plots in Côte d'Ivoire. The objective of this paper is to explore the importance of explicitly controlling for exogenous shocks to production in technical efficiency estimation. We show how omission of such variables in highly stochastic production environments can lead to serious inferential errors, with potentially significant policy implications. Conventional DEA estimation of a production frontier, followed by second-stage Tobit estimation of the correlates of plot-level technical efficiency, suggest widespread and substantial inefficiency related to managerial characteristics and practices. However, when one controls for unobserved groupwise cross-sectional and intertemporal heterogeneity and introduces observable exogenous shocks into the second-stage estimation, managerial characteristics become jointly insignificant and state-conditional technical efficiency becomes nearly universal. The implication is that conventional technical efficiency estimates that refute the classic Schultzian "poor but efficient" hypothesis may be incorrect because they ignore farmers' vulnerability to adverse states of nature against which they cannot insure.

Key words: Africa (Sub-Saharan), Ivory Coast, production frontiers, agricultural productivity, rice.

JEL Codes: O12, Q12, D2

Exogenous Production Shocks and Technical Efficiency Among Traditional Ivorien Rice Farmers

1. Introduction

A considerable empirical literature reports estimates that suggest widespread and substantial farm inefficiency in low-income agriculture, contrary to T.W. Schultz's classic "poor but efficient" hypothesis (Ali and Byerlee 1991). Schultz (1964) argued that traditional farmers, given a long enough period of time to learn their production process, will identify their respective optimal input and output bundles. Thus, Schultz recommended that agricultural development policy focus on expanding peasants' production frontiers. Hence the Green Revolution. However, countless empirical studies have rejected the Schultzian hypothesis. The methods used in estimating allocative and scale efficiency in this context have been recently critiqued (Barrett 1997). This paper takes the next step of considering how estimates of technical efficiency may be affected by measurable exogenous shocks to production (e.g., pest and weed infestation, disease, and rainfall) and by unobserved cross-sectional and intertemporal groupwise heterogeneity. We find that failure to control for these factors in highly stochastic production environments may bias estimates of technical efficiency downward, leading to potentially misguided policy and to misallocated resources.

This paper is an initial attempt at exploring the consequences of exogenous shocks to stochastic production environments in the estimation of productive efficiency. We employ a number of simplifying assumptions — notably the complete exogeneity of environmental shocks — toward which future refinements need to be directed. The objective of this paper is simply to demonstrate the need to account explicitly for potentially exogenous states of nature in technical efficiency estimation.

2. Stochastic Production Technologies and the Estimation of Technical Efficiency

Farmers everywhere are subject to natural shocks to production associated with climate, pests, plant disease, weeds, etc. Peasant farmers in tropical settings are perhaps unusually vulnerable to the realization of these adverse states of nature, both because climatic and epidemiological variability tends to be greater in tropical than in temperate zones and because underdeveloped financial systems limit the capacity to insure. The core observation motivating this paper is that the stochastic production environment has not been satisfactorily addressed in the literature estimating farmers' technical efficiency.

Suppose a farmer generates output, Y, from a production function defined over inputs, X, and exogenous states of nature, W, adjusted for the farmer's technical inefficiency, u ($u \leq 0$). Given mean zero, symmetric sampling and measurement error, v, in the data set, this relationship can be estimated econometrically as $Y = f(X;W)+u+v$. Because the literature has generally paid little attention to the exogenous shocks affecting output, the relation typically estimated is actually $Y = g(X)+\hat{u}+\hat{v}$. While it is useful to know the extent of technical inefficiency prevailing in a sector, policy makers would also like to know the correlates of technical inefficiency in order to target interventions appropriately to reduce estimated inefficiency. The second-stage relation to be estimated is thus $u = h(Z)+\epsilon$, where Z is a vector of farmer characteristics and practices, and ϵ is a white noise error term. But this is commonly done by estimating $\hat{u} = j(Z)+\hat{\epsilon}$. Policy implications are then drawn from the g(X), $\hat{u}$ and j(Z) estimates although, in general, $f(X;W) \neq g(X)$, $u \neq \hat{u}$, and $h(Z) \neq j(Z)$.

When relevant, measurable exogenous shocks, W, are omitted from the first-stage estimation, this necessarily biases estimates of technical inefficiency, unless W and v are identically distributed, at least up to location (mean) and scale (variance) parameters. Because v is typically assumed to be symmetrically (e.g., normally) distributed, and exogenous shocks are commonly asymmetric (see Figure 1 for evidence from this data set), technical efficiency estimates will therefore be biased, as manifest in a statistically significant relation between $\hat{u}$ and W. In this paper, we demonstrate how the omission of exogenous shocks

to production, W, in the estimation of a nonstochastic, nonparametric production frontier affects estimates of u and h(Z).

Let us briefly confront an anticipated, legitimate criticism of our approach. While conventional estimation methods assume farmers suffer no exogenous shocks to production, here we assume that they can do nothing to mitigate those shocks (e.g., apply pesticides to guard against pests). Surely, there is a certain amount of endogeneity in the experience of adverse states of nature. We ignore that here because we aim only to make the simple point that overlooking exogenous shocks to production in highly stochastic environments may lead to serious inferential errors. In extensions underway, we tackle the endogeneity issue directly.

3. Data

The West Africa Rice Development Association (WARDA) farm management and household survey (FMHS), based on three agroecological zones (humid Equatorial forest, sub-humid Guinean savanna, and a transition zone), covers 120 randomly selected rice-producing households in Côte d'Ivoire, and is described in WARDA (1997). Twenty-two surveys were administered annually for the period 1993-1995, covering 1,218 individual plots, 589 of which were planted with rice. Due to nonsystematically missing or incomplete data, or mechanization (we examine only traditional rice farmers), 492 of the 589 rice plots are used in estimating the production frontier, and only 464 of the remaining 492 rice plots are used in the second-stage estimation because data on pests, weeds, or disease are missing in the other 28.

A comparative advantage of the WARDA FMHS is its inclusion of quarterly plot-level measurements of production shocks, such as pest, weeds, and plant disease. As is probably generally the case, these exogenous production shocks are asymmetrically distributed (see Figure 1), with statistically significant positive skewness. So the econometric problems of the previous section exist in this data set, with an uncommon opportunity to check the consequences of the omission of measurable states of nature.

4. Data Envelopment Analysis

Most of the efficiency estimation literature relies on parametric, stochastic estimation methods, following the work of Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977). Because our estimates using those methods — employing a variety of functional forms for the production frontier and several distributional assumptions regarding u — failed to satisfy the basic monotonicity and concavity properties of production functions (Sherlund 1998), we opt instead for a nonparametric estimation approach.

Data envelopment analysis (DEA) requires no *a priori* assumptions regarding either the functional form of the production frontier or the probability density function of the asymmetric technical inefficiency population parameter. DEA is a mathematical programming approach to estimating the convex hull of a data set, imposing (weak) monotonicity and concavity (Färe, Grosskopf, and Lovell 1994).

The output-oriented, variable returns to scale, strong disposability DEA model may be written:

$$\theta^*(X_n,Y_n|VRS,SD) = \max_{\theta,z} \theta, \quad (1a)$$
$$\text{subject to:} \quad \theta Y_n \leq zY, \quad (1b)$$
$$zX \leq X_n, \quad (1c)$$
$$\textstyle\sum_n z_n = 1, \quad (1d)$$
$$z \in \Re^N_+, \text{ where } n=1,...,N, \quad (1e)$$

where z is the activity vector. The resulting output measure of technical efficiency is bounded from below at one, $\theta^* \in [1,\infty)$, representing the multiple by which output may be expanded, holding the input bundle constant. Excluding constraint (1d) yields an analogous constant returns to scale model. However, by applying Banker's (1996) hypothesis testing method to the θ^*s, we reject the null hypothesis of constant returns to scale in favor of the variable returns to scale specification (Sherlund 1998).

We emphasize the importance of accounting for measurable exogenous environmental characteristics. It is also possible, however, that unobserved heterogeneity affects estimation results. While we cannot incorporate observation-specific fixed effects in a model seeking to identify observation-specific inefficiency, u, because of prospective underidentification, we can control for groupwise

unobserved heterogeneity. So we estimated the θ*s in the pooled data set and then tested for statistically significant differences across the three distinct agroecological regions, the three years over which the data were collected, or both, using bootstrapping methods (Atkinson and Wilson 1995, Efron and Tibshiriani 1993). Table 1 presents strata-specific mean technical efficiency scores and 95-percent confidence band bounds. This reveals underlying structural differences in mean technical efficiency scores across regions and time that are statistically significant, as reflected by non-overlapping 95-percent confidence bands on the empirical distribution of the strata means. The transition zone exhibits higher output-oriented mean technical inefficiency scores than either the sub-humid Guinean savanna or humid Equatorial forest agroecologies. This result may be due to agroecological or climatic differences, remoteness of plots from the main village, or possible differences in supporting infrastructures. Similarly, technical inefficiency was more pronounced in 1994, probably due to the January 1, 1994, CFA Franc devaluation (from 50:1 CFA Franc:French Franc to 100:1 CFAF:FF). Given the apparent presence of both cross-sectional and intertemporal groupwise heterogeneity in the pooled data, we stratify the data into nine region-and-year-specific subsamples and reestimate the DEA model of equation (1). Banker's method again rejects the null hypothesis of constant returns to scale in favor of variable returns to scale (Sherlund 1998).

Controlling for unobserved groupwise heterogeneity within the data yields a sharp improvement in the estimated technical efficiency of these rice plots. The first and third rows of Table 2 show the summary statistics for the estimated θ*s from the pooled data; the second and fourth rows show the equivalent estimates from the stratified estimation. The mean, the median, and the 70th and 80th percentile estimates have all fallen markedly, while the proportion of the sample plots lying within one or two standard deviations of perfect efficiency (θ*=1) rises sharply. The mean technical efficiency parameter estimate, for example, falls from 2.59 to 1.39, implying that rather than 159-percent possible expansion in rice output from current input levels implied by conventional estimation, at best a 39-percent expansion is possible once one controls for unobservable groupwise heterogeneity. Similarly, where pooled estimation suggests

11.2-percent of the rice plots are grossly inefficient, the stratified estimation suggests only 4.8-percent of the rice plots lie more than two standard deviations from full technical efficiency. Even though no control has yet been made for measurable exogenous shocks to production, these figures already make Schultz's "poor but efficient" hypothesis appear far more plausible than do the conventional, pooled DEA estimates of the sort reflected in the broader literature.

5. Correlates of Technical Inefficiency

The next logical step is to identify the correlates of technical inefficiency. This is commonly done by estimating a second-stage relationship between the technical inefficiency estimates, $\hat{u}$, and the suspected correlates of technical inefficiency, Z. Statistically significant correlates of estimated technical inefficiency are used to target policy interventions intended to improve sectoral productivity. But if omission of measurable exogenous shocks biases the estimates of u, this may lead to spurious estimated relationships between $\hat{u}$ and Z and, thereby, to misguided policy recommendations.

We investigate that possibility by running two different regressions of the θ^*s ($\hat{u}$ in our DEA model). First, we regress θ^* on managerial characteristics (e.g., age, gender, education, and experience), and managerial practices (e.g., type of seed used, number of plots and crops cultivated), all of which either describe or are under the short-run control of the plot manager. This replicates the conventional second-stage estimation found in the literature and, as we show momentarily, generates reasonably typical results. Then, we introduce exogenous shock variables representing plot characteristics (e.g., erosion, fertility, soil aptitude, slope, and topographic location), states of nature (e.g., pests, weeds, disease, and rain), and region and year controls, all of which are largely (or entirely) outside the control of the plot manager. This second regression allows us to establish whether exogenous shocks are correlated with the conventional first-stage estimates of technical efficiency and, more strongly, to test the hypothesis that the managerial characteristics and practices variables are jointly statistically insignificant. We find that not only are

exogenous variables significantly correlated with estimates of technical inefficiency, but that when exogenous variables are appropriately controlled for, managerial variables are jointly statistically insignificant. Omission of the exogenous states of nature variables, W, from the first-stage production frontier estimation appears to bias conventional estimates of both technical efficiency and its relationship to managerial characteristics and practices, potentially flawing policy-related inference.

Measurement error, sampling error, and the unobservability of the true production frontier, make it possible that the natural logarithm of an observation's true technical efficiency measure, ln(u), is less than zero, although it cannot be observed directly in the constructed $\ln(\theta^*)$ variable. The estimated technical efficiency parameter is thus a censored variable, so we estimate the following Tobit model:

$$\ln(\theta^*) = \psi + M\alpha + W\delta + \tau, \text{ if } >0, \quad (2a)$$
$$\ln(\theta^*) = 0, \text{ otherwise}, \quad (2b)$$

where M is a vector of managerial characteristics and practices variables, W is a vector of exogenous shock variables, τ is a Gaussian white noise error term, and ψ, α, and δ are estimable parameters. Note that because $\theta^* \in [1,\infty)$, $\ln(\theta^*) \in [0,\infty)$.

Table 3 presents three different sets of regression results. The leftmost column presents the estimates of the conventional model, using the θ^* derived from the pooled data — i.e., failing to control for unobserved groupwise heterogeneity — and implicitly setting $\delta=0$. The central column presents estimates that use the θ^* derived from the stratified frontier estimation, but still setting $\delta=0$. The rightmost column shows the estimates that result from the use of the θ^* derived from the stratified frontier estimation and the relaxation of the standard $\delta=0$ assumption.

The first thing to note is that while several managerial characteristics and practices have statistically significant relationships to technical inefficiency in the absence of controls for exogenous shocks, none do in the most general specification. Women, the very young or old (estimated θ^* is minimized at age 49, according to the middle column specification), and those who engage in considerable

multicropping appear to be less efficient in the absence of controls for exogenous shocks. Such results are commonplace in the literature (Ali and Byerlee 1991, Barrett 1997) and give rise to policy recommendations emphasizing targeted farmer education and extension programs. Once such controls for exogenous shocks are added, however, we find that a plot's location on the hydromorphic or lowland toposequence, low rainfall (estimated θ^* is maximized near the minimum rainfall quantity), high rates of pest infestation, and steep plot slopes are the only statistically significant correlates of θ^*, individually or jointly. This shift may capture the social dynamics of land allocation, wherein the less powerful (the elderly, the young, and women) are allocated less desirable plots, particularly with poorer water control. But the crucial issue appears to be not managerial characteristics or practices so much as the experience of adverse exogenous production shocks. The policy implication of our findings is that improved water, pest control, and terracing technologies hold the key to improving yields, given current production technologies.

The second point is stronger still. A likelihood ratio test of the joint null hypothesis that $\delta=0$, i.e., that the exogenous shock variables are jointly statistically insignificant, as is implicitly assumed in most of the literature, yields a test statistic (p-value against the $\chi^2(24)$ distribution) of 106.75 (0.0000), enabling the rejection of the null hypothesis. In other words, the exogenous variables, as a group, have a statistically significant relationship with technical inefficiency estimates. Since W and u must be orthogonal in the true population relationship, the statistically significant relation between $\hat{u}=\theta^*$ and W demonstrates that omission of states of nature from the estimation of inherently state-conditional frontiers biases plot-level technical efficiency estimates.

By contrast, the likelihood ratio test statistic on the joint null hypothesis that $\alpha=0$ is only 19.20, for a p-value of 0.2585 against the $\chi^2(16)$ distribution. One cannot reasonably reject the null hypothesis that managerial characteristics and practices, as a group, do not have a statistically significant relationship with estimated technical inefficiency. These results challenge orthodox notions of targeted extension service and farmer education programs as an effective means to increase sectoral efficiency without necessarily

augmenting the production technology. Our results imply instead a need for technological improvements in farmers' capacity to control their production environments and in overall output capacity (i.e., an outward shift in the production possibilities frontier).

6. State-Conditional Technical Efficiency

By taking the estimates of θ^* and δ, along with equation (2a), we can indirectly estimate the true plot-specific state-conditional technical efficiency (SCTE), u, as:

$$SCTE = \theta^*|W = (\theta^*)\exp\{-\delta(W-W^*)\}, \tag{3}$$

where W* is the estimated optimal state of nature, as identified by the first derivative of equation (2a) with respect to each exogenous variable. Recall that $\theta^* \in [1,\infty)$, thus, $SCTE \in (0,\infty)$. Indexing estimated state-conditional technical efficiency to the estimated (state unconditional) best-practice frontier, we define SCTE*=SCTE if SCTE>1 and SCTE*=1 if $SCTE \in (0,1]$. In words, if under a better draw of production environments the plot's output is estimated to be at least as great as one would predict from realized best practices, we consider the plot to be technically efficient.

As shown in Table 4, mean SCTE and mean SCTE* are much lower than mean θ^*. The estimated multiple by which mean plot output can be expanded has dropped from 1.3861 to only 1.0004. Note that the naive DEA estimates of mean θ^* — without controls for unobserved groupwise heterogeneity or adjustment for within sample variation in exogenous shocks — were 2.5861. Rather than the 159-percent estimated output expansion possibility suggested by the DEA estimation method common in the literature, our state-conditional method suggests there is effectively no room for output expansion under current technologies without improved methods for controlling producers' environments. Put differently, the rice farmers of this data set are largely managerially efficient; unobserved groupwise heterogeneity and observable environmental shocks to production explain effectively all of the observed deviations from the best-practice production frontier.

7. Conclusions

This paper is motivated by a concern that the empirical literature on technical efficiency estimation of peasant agriculture largely ignores that production decisions are made in and data are drawn from highly stochastic production environments. We first explain why prevailing empirical methods, using either econometric or programming techniques, may yield biased and inconsistent estimates of technical efficiency, production frontiers, and the relationship between estimated technical efficiency and managerial characteristics and practices. This may have serious implications for policy makers relying on statistical inference from such models to guide resource allocation in agricultural development. We then demonstrate the relevance of our concern to the important case of west African rice production. Using a unique panel data set of 492 Côte d'Ivoire rice plots, we show that failure to control for unobserved cross-sectional and intertemporal groupwise heterogeneity yields highly inflated estimates of technical inefficiency. Similarly, failure to control for observable exogenous production shocks leads to biased estimates of plot-level technical efficiency and to spuriously significant relationships between managerial characteristics and practices and plot-level technical inefficiency. We introduce a new, indirect measure of state-conditional technical efficiency that reflects only those factors controllable by plot managers. Mean state-conditional technical efficiency is estimated at 1.0004 — as compared to mean (state-unconditional) estimates of 2.8716 using conventional methods — suggesting that the rice farmers in this survey are largely managerially efficient.

These results have significant policy implications. Conventional methods of estimating production frontiers, technical inefficiency in production, and the correlates of technical inefficiency suggest that the traditional Ivorien rice farmers we study are highly inefficient, leaving open the question of whether scarce agricultural development funds are best spent to develop improved technologies or to teach farmers how better to use existing technologies. By controlling for unobserved and observed exogenous shocks to production, however, we find instead that almost all of these rice producers are wholly state-conditional

technically efficient, implying they can be made better off only through the expansion of the production frontier or through improvements in their capacity to control a highly stochastic production environment. Schultz appears to be right when one compares Ivorien rice producers against the estimated stochastic production frontier they actually face, given their idiosyncratic realization of the environmental conditions vector, W, rather than against the state-unconditional best-practice frontier, which implicitly pits them against colleagues enjoying considerably more favorable exogenous shocks to production.

References

Aigner, D.J., Lovell, C.A.K., and Schmidt, P. (1977). 'Formulation and estimation of stochastic frontier production function models', *Journal of Econometrics*, **6**, 21-37.

Ali, M. And Byerlee, D. (1991). 'Economic efficiency of small farmers in a changing world: a survey of recent evidence', *Journal of International Development*, **3**, 1-27.

Atkinson, S.E. and Wilson, P.W. (1995). 'Comparing mean efficiency and productivity scores from small samples: a bootstrap methodology', *Journal of Productivity Analysis*, **6**, 137-152.

Banker, R.D. (1996). 'Hypothesis tests using data envelopment analysis', *Journal of Productivity Analysis*, **7**, 139-159.

Barrett, C.B. (1997). 'How credible are estimates of peasant allocative, scale, or scope efficiency? A commentary', *Journal of International Development*, **9**, 221-229.

Efron, B. And Tibshiriani, R.J. (1993). *An Introduction to the Bootstrap*. New York, NY: Chapman and Hall.

Färe, R., Grosskopf, S., and Lovell, C.A.K. (1994). *Production Frontiers*. Cambridge, MA: Cambridge University Press.

Meeusen, W. And van den Broeck, J. (1977). 'Efficiency estimation from Cobb-Douglas production functions with composed error', *International Economic Review*, **18**, 435-444.

Schultz, T.W. (1964). *Transforming Traditional Agriculture*. New Haven, CT: Yale University Press.

Sherlund, S.M. (1998). 'Exogenous shocks and technical efficiency among Ivorien rice farmers', M.S. thesis, Logan, UT: Utah State University.

WARDA. (1997). 'WARDA/ADRAO farm management and household survey data guide', Bouaké, Côte d'Ivoire: West Africa Rice Development Association.

Figure 1: Distributions of Asymmetric Exogenous Shocks

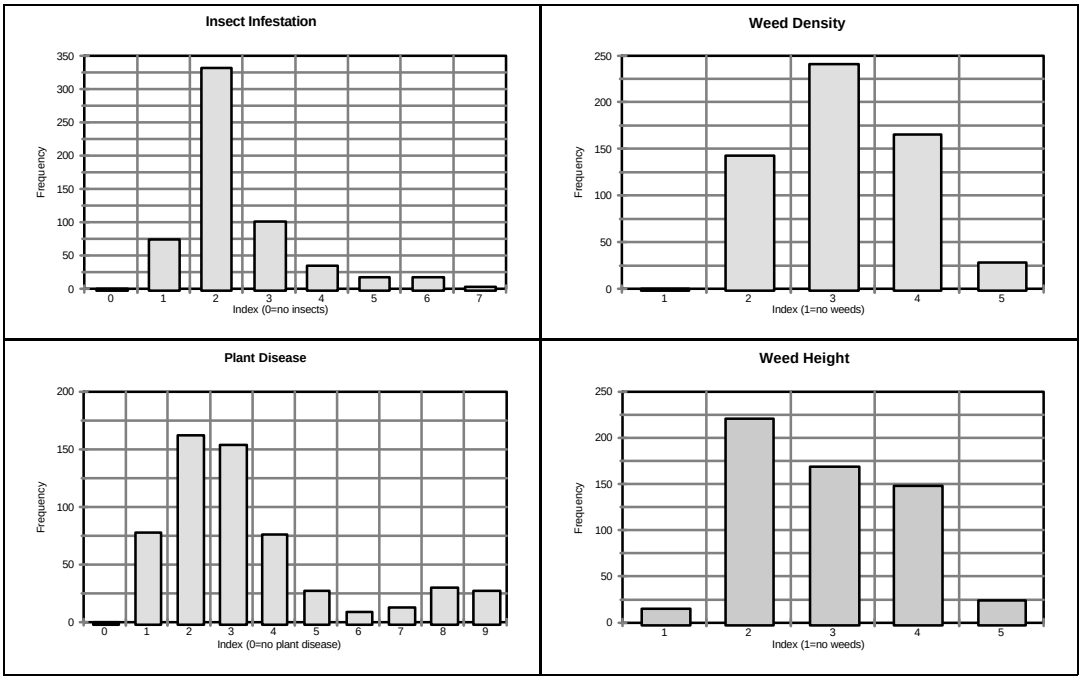

Table 1: Bootstrapping Technical Efficiency Scores--95 Percent Confidence Bands

Stratus	Mean	Lower Bound	Upper Bound	No. Obs.
Sub-humid	2.2754	2.0379	2.5437	119
Transition	2.9157	2.6050	3.2547	181
Humid	2.4695	2.3231	2.6175	192
1993	2.1581	1.9406	2.3861	118
1994	2.9883	2.7083	3.2931	194
1995	2.4324	2.2447	2.6317	180
1993-SH	1.9949	1.7184	2.3087	33
1993-TR	2.6717	2.2202	3.1475	47
1993-HU	1.6675	1.5017	1.8529	38
1994-SH	2.4444	1.9641	3.0049	46
1994-TR	3.5083	2.8810	4.2046	68
1994-HU	2.8628	2.6165	3.1180	80
1995-SH	2.3111	1.9531	2.7215	40
1995-TR	2.4759	2.0764	2.9285	66
1995-HU	2.4565	2.2627	2.6558	74

SH=Sub-humid region, TR=transition region, HU=humid region.

Table 2: Stratified Output-Oriented Technical Efficiency Summary Statistics

	70th Percentile	80th Percentile	Inside 1 St. Dev.	Inside 2 St. Devs.
Pooled Results	1.6747	1.3267	0.6524	0.8882
Stratified Results	1.0000	1.0000	0.8476	0.9512

	Mean	Median	St. Dev.	Skewness	Rel. Kurt.	Min.	Max.	Number
Pooled Results	2.5861	2.1882	1.6748	2.9015	15.0110	1.0000	16.6941	492
Stratified Results	1.3861	1.1696	0.7267	6.5646	71.9108	1.0000	11.1980	492
1993-SH	1.1971	1.0886	0.2363	1.2003	0.8920	1.0000	1.8761	33
1993-TR	1.2187	1.0000	0.3961	2.1743	4.4205	1.0000	2.6867	47
1993-HU	1.3126	1.1470	0.4219	2.0462	4.5731	1.0000	2.8864	38
1994-SH	1.5865	1.3599	0.7857	2.5202	7.2591	1.0000	4.6563	46
1994-TR	1.4594	1.0436	1.4033	5.6367	35.4496	1.0000	11.1980	68
1994-HU	1.6527	1.5819	0.5212	1.0523	1.0098	1.0000	3.2433	80
1995-SH	1.7217	1.4088	0.8750	1.2755	0.8141	1.0000	4.3509	40
1995-TR	1.0869	1.0000	0.1286	1.6118	1.8816	1.0000	1.4733	66
1995-HU	1.2199	1.1500	0.2602	1.9774	5.6240	1.0000	2.4348	74

SH=Sub-humid region, TR=transition region, HU=humid region.

Table 3: Second-Stage (Tobit) Estimation Results

Variable	Pooled M only	Stratified M only	Stratified M and W	Variable	Pooled M only	Stratified M only	Stratified M and W
Constant	1.0458 (3.109)***	0.4004 (1.506)	-31.0268 (-2.494)**	Pests (1=good, 7=severe)			0.1902 (2.263)** [6.32]**
Modern (% of seed modern)	-0.0096 (-0.566) [9.44]***	-0.0002 (-0.013) [0.01]	-0.0017 (-0.147) [0.83]	Pests^2			-0.0213 (-1.822)*
Modern^2	0.0001 (0.462)	0.0000 (0.016)	0.0000 (0.189)	Weed Dens. (1=good, 5=severe)			-0.3234 (-1.556) [2.53]
Experience (years with rice variety)	0.0173 (0.789) [0.65]	0.0170 (0.971) [1.41]	0.0062 (0.377) [0.14]	Weed Dens.^{2}			0.0480 (1.563)
Experience^2	-0.0009 (-0.674)	-0.0012 (-1.152)	-0.0003 (-0.334)	Weed Height (1=good, 5=severe)			-0.0893 (-0.674) [1.82]
Gender (0=M, 1=F)	-0.0616 (-0.769)	0.1470 (2.312)**	-0.0279 (-0.414)	Weed Hght.^{2}			0.0201 (0.944)
Age (years)	-0.0066 (-0.488) [1.04]	-0.0246 (-2.292)** [5.45]*	-0.0134 (-1.387) [2.28]	Plant Dis. (1=good, 9=severe)			0.0210 (0.411) [0.27]
Age^2	0.0001 (0.640)	0.0003 (2.347)**	0.0001 (1.475)	Plant Dis.^{2}			-0.0015 (-0.299)
Elem. Edu. (0=N, 1=Y)	-0.0366 (-0.336) [7.149]	-0.0196 (-0.227) [6.34]	-0.0315 (-0.403) [6.33]	Hydromorph (0=N, 1=Y)			-0.3800 (-2.861)*** [16.83]***
Sec. Edu. (0=N, 1=Y)	0.1301 (1.144)	0.0863 (0.967)	0.0477 (0.591)	Lowland (0=N, 1=Y)			-0.1452 (-2.325)**
Inc. College (0=N, 1=Y)	-0.0749 (-0.628)	0.0095 (0.098)	0.0648 (0.735)	Irrigated (0=N, 1=Y)			0.2077 (0.503)
College (0=N, 1=Y)	-0.4098 (-1.192)	-0.2493 (-0.891)	-0.2246 (-0.789)	Rain Days (number)			0.4119 (1.704)* [7.01]**
Prof. Degree (0=N, 1=Y)	0.4547 (1.863)*	0.1543 (0.807)	0.1246 (0.715)	Rain Days^2			-0.0020 (-1.740)*
Plots (number)	-0.1480 (-0.789) [8.54]**	-0.2263 (-1.441) [6.50]**	-0.0398 (-0.275) [0.11]	Rainfall (cm)			0.2020 (4.607)*** [21.13]***
Plots^2	-0.0031 (-0.132)	0.0142 (0.740)	0.0033 (0.193)	Rainfall^2			-0.0009 (-4.464)***

Crops (number)	0.1193 (0.576) [3.58]	0.3867 (2.241)** [10.47]***	0.1690 (1.046) [2.48]	Transition Zone (0=N, 1=Y)			0.6928 (0.976) [3.53]
$Crops^2$	0.0003 (0.010)	-0.0332 (-1.438)	-0.0292 (-1.411)	Humid Zone (0=N, 1=Y)			0.0680 (0.208)
Erosion (0=N, 1=Y)			0.0330 (0.475)	Year 1994 (0=N, 1=Y)			0.3780 (1.227) [4.97]*
Fertility (1=good, 2=fair, 3=poor)			0.0412 (0.993)	Year 1995 (0=N, 1=Y)			-0.0217 (-0.195)
Aptitude (see fertility)			-0.0032 (-0.074)	σ	0.5548	0.4191	0.3639
Slope (percent)			0.0048 (0.274) [6.19]**	ℓ=ln(L)	-400.3906	-295.4569	-242.0799
$Slope^2$			-0.0009 (-1.251)				

***, **, * = statistically significant at the 99, 95, and 90 percent confidence levels, respectively.

t-ratios in parentheses, likelihood ratio statistics for joint hypothesis tests of significance of each quadratic variable expression and each group of binary variables in brackets.

Table 4: State-Conditional Technical Efficiency Summary Statistics

	Mean	Median	Standard Deviation	Minimum	Maximum
θ* (pooled)	2.5861	2.1882	1.6748	1.0000	16.6941
θ* (stratified)	1.3861	1.1696	0.7267	1.0000	11.1980
SCTE	0.1911	0.1508	0.1092	0.0654	1.1862
SCTE*	1.0004	1.0000	0.0086	1.0000	1.1862