Technical Efficiency in Agricultural Production and Its Determinants: An Exploratory Study at the District Level

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Abstract

Given the importance of agriculture to the well being of a large percentage of India's population, it becomes important to study how improvements can be made in the productivity of this sector. This study attempts to estimate the technical efficiency – a measure of how well inputs are being used towards producing output – of about 250 Indian districts in 1990-91. It employs the stochastic frontier function methodology. The results indicate that (i) the land elasticity is the highest followed by fertilizer; (ii) the mean efficiency of raising agricultural output is 79 per cent and therefore there is a scope for increasing output by 21 per cent without additional resources; (iii) states such as Madhya Pradesh, Uttar Pradesh, and Rajasthan have the largest number of districts with below average TE and they stand to gain the most from policy interventions towards improving technical efficiency. The results further indicate that health, education, and infrastructure are powerful drivers of efficiency at the district level and the relative importance of the determinants of efficiency across districts depends greatly on environmental factors, such as agro-climatic zones, technological factors, and crop mix. The results highlight the need for developing policy strategies at a more localized level.

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1. Introduction

Agriculture continues to dominate the economic scene of India, accounting for about one-third of GDP and one-fifth of foreign exchange. This sector provides employment to more than 70 percent of the total labour force in the country. Furthermore, its forward and backward linkages with other sectors of the economy are well established in the development economics literature. Therefore, to achieve an accelerated pace of economic growth, sustained development of the agriculture sector is *sine quo non*.

Reform measures implemented in the industrial, financial, and trade sectors would definitely contribute to the agricultural growth through agricultural prices and income. However, various non-price, institutional, and organizational factors are also important for the sustainability of agricultural growth. For instance, the efficiency of production is extremely important for output growth: using existing resources in the best possible manner would yield the highest possible output for the given technological constraints.

International comparisons indicate that agricultural productivity in India is relatively low. For instance, although India has the largest area under cereal cultivation (99.45 million ha.), the average yield of cereal production in 1998 (2206 kg/ha.) was lower than the world average for that year (2959 kg/ha.).[1] One important reason for low productivity is that many farmers with low literacy rates and inadequate physical infrastructures face difficulties in understanding new technologies and, therefore, fail to fully exploit these technical opportunities.[2] In the light of these facts, it is clear that an increase in agricultural production can come from an increase in production efficiency. Hence, it is essential to assess how existing inputs are being used, and what possibilities exist for improving efficiency of agricultural production in India, given resource constraints.

The efficiency of a farm/production unit can be measured in terms of allocative efficiency (reflecting the ability of a farm to use inputs in optimal proportions, given their respective prices) and technical efficiency (TE). In this study, we focus on the latter (i.e., TE). Briefly, the TE is the ratio between actual and potential output of a production unit. A few empirical studies provide the estimates of TE of raising a particular crop (mostly rice) within a state/region. For instance, Kalirajan (1981), Shanmugam and Palanisamy (1993), Tadesse and Krishnamoorthy (1997) and Mythili and Shanmugam (2000), estimated the TE of rice farms in Tamil Nadu. Datt and Joshi (1992) measured the TE of rice farms in Uttar Predesh while Jayaram et al., (1987) and Shanmugam (2002) measured the TE of raising rice crop in Karnataka. Shanmugam (2000) estimated the efficiency of rice farms in Bihar. An exception is Shanmugam (2003), which provides TE of rice, cotton and groundnut growing farms in Tamil Nadu. The results of these studies are useful for policy makers to rationalize the development policies for a particular crop in region.

However, no attempt has been made to analyze the efficiency of agricultural production as a whole at district level. In this study, we attempt to measure the TE of agricultural production in various districts in India. We also attempt to identify various socioeconomic and ecological factors determining the TE levels in various districts. Such information can be useful to identify the districts with low efficiency and suggest measures to improve the efficiency of those districts.

This study represents a departure from existing studies on the topic in that it considers entire districts as the producing “units”.[3] Also, it introduces health status as one of the determinants of efficiency in addition to education, land holding, agro-climatic zone, etc.[4] Cross-country and micro level evidences clearly indicate that health significantly influences economic performance (Barro and Xala-i-Martin, 1995; Bloom et al., 2001; Bhargava et al., 2001; Deolalikar, 1988). Several State level studies for India have shown similar results, *albeit not* so emphatically (Nagaraj et al.,2000; Gupta and Mitra, 2001 and Mitra et al., 2002).[5]

As Bloom and Canning (2000) point out, health is a factor that positively influences economic performance through enhancing labour productivity and returns to education. The aforementioned studies typically consider health status as a direct input to production/growth and at least one study has cited this as being problematic in terms of interpreting the ensuing results.[6] Our specification suggests a way around this issue by modeling health as a factor that influences production indirectly, through direct effects on TE.[7]

The remainder of this study proceeds as follows. Section 2 provides a brief review of literature relating to the concept of TE and its measurement. Section 3 explains the methodology employed in this study to estimate district specific TE. Data, modeling strategy, and variables are discussed in Section 4. Section 5 provides the empirical results and Section 6 summarizes the findings and discusses policy implications.

2. Literature Review

According to the literature, the efficiency of a farm (production unit) can be measured either with respect to its normatively desired performance or with the performance of another farm. Thus, measures of efficiency are essentially computed by comparing observed performance with some specified standard notion of performance. The "production frontier" serves as one such standard in the case of TE. TE can be defined as the ability and willingness of a production unit to obtain the maximum possible output with a specified endowment of inputs (represented by a frontier production function), given the surrounding technology and environmental conditions.[8]

Suppose that a farm has a production plan (Y°, X°), where the first argument is the set of outputs and the second represents the set of inputs. Given a production function f (.), the farm is technically efficient if $Y^\circ = f(X^\circ)$ and technically inefficient if $Y^\circ < f(X^\circ)$. Therefore, the TE can be measured by the ratio $0 \leq Y^\circ / f(X^\circ) \leq 1$. Farrell (1957) carried out the first empirical study to measure TE for a cross-section of production units by using a deterministic/non-parametric frontier approach and, consequently, frontier efficiency comparisons have become synonymous with the term "Farrell efficiency measurement". This measure assumes that the production function of the fully efficient unit is known in some manner. Since this bench mark of frontier production function is never known in practice, Farrell suggests that it can be estimated from sample data using either a non-parametric piece-wise linear technology or by a parametric function such as the Cobb-Douglas form.

Aigner and Chu (1968) followed the latter method and estimated a deterministic parametric frontier using a homogeneous Cobb-Douglas production function. Later, Timmer (1971) converted the deterministic frontier into a probabilistic frontier method. However, this approach has some limitations. All farms share a common frontier and variations in farm efficiency are measured relative to this frontier. This approach ignores the random factors that can influence the efficiency of a farm (such as climate). Moreover, the results of this approach are highly sensitive to variable selection and data errors.

Later, Aigner, Lovell, and Schmidt (1977) and Meeusen and Broeck (1977), independently developed a stochastic frontier approach to measure TE. This approach introduces TE as a multiplicative (neutral) shift variable within a production function framework. This means that the input coefficients of the conventional production function and that of the frontier function are the same and only the intercept term changes.[9] In practice, with cross-section data, the distribution of the TE term must be specified - as half-normal, truncated normal, or otherwise. As suggested independently by Jondrow et al. (1982) and Kalirajan and Flinn (1983), one can calculate individual-specific TE values by using this procedure. This particular approach has been extended in various ways, such as the specification of more general distributions for the residual term (exponential and gamma), the consideration of panel data for analysis, and the measurement of TE using cost/profit functions. A number of comprehensive literature reviews are available, such as Forsund et al. (1980), Bauer (1990), Battese (1992), Greene (1993) and Kalirajan and Shand (1994).

3. Methodology

This study uses the stochastic (or econometric) frontier production function model for cross sectional data. We define the frontier production function as the maximum feasible or potential output that can be produced by a production unit such as farm, given level of inputs and technology. The actual production function (corresponding to the production unit's actual output) can be written as:

$$Q_i = f(X_i; \beta) \exp(-u_i) \text{ and } 0 < u_i < \infty;\ i = 1,2,\ldots,n. \qquad (1)$$

where Q_i represents the actual output for the i^{th} sample (production) unit; X_i is a vector of inputs and β is a vector of parameters that describe the transformation process; f (.) is the frontier production function and u_i is a one-sided (non-negative) residual term. If the production unit is inefficient, its actual output is less than the potential output. Therefore, we can treat the ratio of the actual output Q_i and the potential output f(.) as a measure of the technical efficiency of the production unit. Using equation (1) above, we can write this measure as:

$$TE = Q_i / f(X_i; \beta) = \exp(-u_i) \qquad (2)$$

Notice that u_i is zero if the production unit produces the potential output (full TE) and is less than zero when production is below the frontier (less than full TE). A random noise variable v_i (independently and identically distributed normal with mean 0 and variance σ_v^2) can be included in the equation (1) to capture the effect of other omitted variables that can influence the output as:

$$Q_i = f(X_i; \beta) \exp(v_i - u_i), \qquad (3)$$

This new function is known as the individual-specific stochastic production frontier function. In order to estimate equation (3), we consider a half normal distribution for u_i (after empirical verification). The likelihood function for this model is:

$$L = -N \text{ In } \sigma - \text{constant} + \sum [\ln \Phi(-\varepsilon_i \lambda / \sigma) - 1/2 (\varepsilon_i / \sigma)^2] \quad (4)$$

where, $\lambda = \sigma_u / \sigma_v$, $\sigma^2 = \sigma_v^2 + \sigma_u^2$, and Φ is the cumulative standard normal distribution function and $\varepsilon_i = (v_i - u_i)$; σ_u and σ_v are standard deviations of the residuals u and v respectively. The maximum likelihood estimation (MLE) method can provide the estimates of the stochastic frontier production equation. The individual specific TE is given by the conditional mean of $\exp(-u_i)$, given the distribution of the composite error term, ε_i.

Some other important parameters of the model are: $\sigma = \sqrt{(\sigma_u^2 + \sigma_v^2)}$, $\lambda = \sigma_u/\sigma_v$ (>0) and $\gamma = (\sigma_u^2/\sigma_v^2)$. A significant σ (and λ) would indicate the significant variations in the output levels. The λ term with value above one would indicate that output variations due to inefficiency are higher than that due to random factors. A zero value of γ would indicate that the deviations from the frontier are due entirely to the noise and, in this case, the ordinary least squares (OLS) estimates of the model are equivalent to the MLE results. A value of one would indicate that all deviations are purely due to differences in TE across farms.

4. Data and Modeling

This study uses district level data, compiled from various secondary sources, for the year 1990-91. Gross agricultural production value (in rupees) measures the aggregate total output variable (Q_i) in the study. Inputs comprise three categories of land, chemical fertilizer, and labour.[10] Land (A) refers to gross sown area (in sq km) and fertilizer (F) refers to the gross weight (in tonnes) of nitrogenous, phosphate and potash fertilizers that each district consumed annually. Labour (L) refers to workers in the cropping sector.[11] The data for these variables were taken from CMIE (1993) and CMIE (2000). Due to missing information, we include input-output data for 248 districts, distributed across 12 major states. Table 1 provides the average values of the study variables in various states in 1991.

Table 1

Mean Values of Study Variables in Various States

State	Value of Output (Rs.)	Land Area (km^2)	Fertilizer (tonnes)	Labour (Nos.)	No. of Districts
Andhra Pradesh	3818402	6237	7202.8	258219	19
Gujarat	2906552	6742	4214.2	171997	16
Haryana	2162786	4230	4222.5	82907	5
Karnataka	3313712	6719	4481.6	153505	17
Maharashtra	2470727	7639	4191.5	183842	24
Madhya Pradesh	1284481	5007	1636.6	78173	41
Orissa	2829269	6953	1616.5	163568	12
Punjab	4402180	5943	9322.3	121269	11
Rajasthan	1520413	7054	1135.8	80074	26
Tamil Nadu	4609755	3692	5293.3	408215	12
Uttar Pradesh	2006992	4191	3608.0	307109	54
West Bengal	4022178	5178	4337.0	559080	11
All-India Average (Standard Deviation)	2532272 (1828697)	5686 (2940)	3737.6 (3169.0)	206898 (192545)	248

Source (Basic Data): CMIE (1993, 2000).

Note that Tamil Nadu had the highest mean value of output while West Bengal had the highest mean value of labour. Madhya Pradesh obtained the lowest mean values of both output and labour. The highest average land area was in Maharashtra and the lowest in Tamil Nadu. The average fertilizer consumption was relatively high in Punjab as compared to other states and low in Rajasthan. Thus, there exists a high degree of variation across states with respect to these indicators.

Our empirical strategy consists of two stages. In the first stage we estimate the stochastic frontier production function and district-specific TE values for agricultural production. We began by considering various functional forms, such as transcendental logarithmic (translog) function and Cobb-Douglas function, and found that the latter provides the best fit. Therefore, our stochastic frontier production function is given by:

$$\ln Q_i = \beta_0 + \beta_L \ln L + \beta_A \ln A + \beta_F \ln F + v_i - u_i. \qquad (5)$$

where β_i's are parameters to be estimated and Q, L, A, and F are as defined above. As mentioned before, the MLE technique is used to estimate (5). In the second stage, we estimate the determinants of TE by regressing the TE values obtained from estimates of (5) on various socioeconomic variables. Since the estimated TE is bounded between 0 and 1, it is specified as follows using suggestions given in literature:

$$\ln[TE_i/(1-TE_i)] = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \alpha_4 X_4 + \alpha_5 X_5 + e_i \qquad (6)$$

where, X_1 is the rural literacy rate (proxy for education), X_2 is the rural infant mortality rate, IMR (proxy for health)[12], X_3 and X_4 are the percentage of villages with pucca road facility and percentage of electrified villages in the district (infrastructure variables), and X_5 represents the average operational holding size in hectares (economic variable). The data source for operational holding size and rural literacy rates is CMIE (1993) and for IMR, Irudaya Rajan and Mohanachandran (1998). The percentage of villages with pucca road access and electricity are gleaned from Government of India (1997). Table 2 reports the means of variables used in the second stage of our analysis. We may again observe that the states vary greatly with respect to all of the socioeconomic and infrastructure variables in considerations.

Table 2

Mean Values of Variables Used in the Technical Efficiency Equation

State	Rural Literacy Rate (%)	Rural Infant Mortality Rate	% Villages with Pucca Roads	% of Villages Electrified	Land Holding Size (ha.)
Andhra Pradesh	35.28	52.58	56.82	74.19	1.73
Gujarat	52.27	71.12	59.48	84.22	3.83
Haryana	47.40	60.20	97.44	95.43	2.70
Karnataka	48.71	64.23	69.34	97.94	2.51
Maharashtra	55.97	67.95	44.20	67.98	2.55
Madhya Pradesh	35.53	116.93	23.26	56.14	3.23
Orissa	44.60	113.75	24.15	21.67	1.49
Punjab	54.36	61.01	95.81	96.80	3.67
Rajasthan	28.96	90.69	31.06	48.38	5.20
Tamil Nadu	58.22	52.17	81.43	79.59	0.99
Uttar Pradesh	38.87	92.83	42.16	49.88	1.04
West Bengal	48.59	70.00	31.55	21.04	1.06
All-India Mean (Standard Deviation)	42.79 (12.53)	83.71 (27.12)	46.23 (23.61)	81.37 (20.30)	2.49 (2.10)

Source (Basic Data): CMIE (1993), Irudaya Rajan and Mohanachandran (1998), and Government of India (1997).

In order to control for agro-climatic variation and differences in irrigation practices according to district, we decide to estimate (6) for different subgroups. For agro-climatic subgroups, we use the designations provided by NBSS and LUP (1992). Here, districts are divided amongst 20 "agro-eco-regions" based on soil type, water resources, topography and climate. These are further grouped into

five bio-climatic types (per-humid, sub-humid, coastal, semi-arid, and arid). For irrigation, we use the designation employed by Fan and Hazell (2000), where districts are grouped as irrigated (over 25% of gross cultivated area irrigated), rain fed high-potential, and rain fed low-potential. For our purposes, we group the latter two into the category "non-irrigated."

The advantages of sub-group analysis, as opposed to controlling for all of these factors in a single model for all districts are two-fold. First, we find that controlling for the irrigation and agro-climatic variables explicitly in a single model adds little information: the variables are generally statistically insignificant. Second, we feel it is quite interesting, especially from a policy standpoint, to consider the differential determinants of production efficiency in the context of different agro-climatic zones and agricultural practice regimes.

Finally, we also extend the idea of sub-group analysis to crop mix. While one can use the stochastic frontier production function across aggregated firms producing similar crops, a problem might arise in our estimation of technical efficiency due to the fact that our measure of production aggregates across the entire crop spectrum. If different TE levels characterize the production processes of different crops, aggregation will leave us with a loss of information. To partially address this question, we group districts into rice plurality (in land use), wheat plurality, and other, and analyze the determinants of efficiency within these groups. In the future, given crop-wise output data at the district level, it may be possible to employ advanced techniques in order to construct more meaningful production aggregates with the appropriate weights (see, for example, Lothgren, 2000). For the purposes of this particular study, the current measure will serve our goals well and the analysis will still be quite insightful.

5. Empirical Results

(i) Estimates of the Frontier Production Function

Table 3 contains our production function estimation results. For comparative purposes, the first column reports the OLS estimates of the average production function given in equation (5). As expected, the estimated parameters of all the input variables are positive. Notably, all of them are statistically significant at 1 per cent level. Land has the largest output elasticity, followed by that of fertilizer.

The MLE results are presented in the second column.[13] The coefficients on the input variables are more or less similar to those estimated by OLS. The elasticity of land, fertilizer, and labour are 0.39, 0.34, and 0.19, respectively. The implicit assumption in our analysis is that there exists Hicks' neutral technical change, which means that the intercept in MLE results should be higher than that in computed by OLS, while the slopes should be more or less equal in both OLS and MLE results. Our results clearly support this assumption.

Table 3

Estimates of the Stochastic Frontier Production Function

Variables	OLS	MLE
	(1)	(2)
Constant	6.2775 (16.460)	6.6639 (14.727)
Ln (LABOUR)	0.1968 (5.484)	0.1884 (6.923)
Ln (AREA)	0.3978 (7.402)	0.3858 (6.861)
Ln (FERTILIZER)	0.3381 (10.243)	0.3416 (10.113)
$\sigma_u/\sigma_v (=\lambda)$	-	0.8105 (1.859)
$\sqrt{\sigma_u^2 + \sigma_v^2}\ (=\sigma)$	-	0.4961 (8.751)
σ_u^2	-	0.0976
σ_v^2	-	0.1486
$\gamma_{(=\sigma_u^2/\sigma^2)}$	-	0.3964
Log-Likelihood	-142.1992	-141.8507
R^2 (F)	0.712 (201.11)	-
Iterations	-	9
Sample Districts	248	248
Mean TE(%)	-	79.32

-Figures in parentheses are the absolute t values (in OLS) and asymptotic t values (in MLE).

Both λ and σ have positive coefficients. σ is statistically significant at 1 per cent while λ is significant only at 10 per cent level. The estimated values of σ_u^2 and σ_v^2 are 0.098 and 0.149 respectively. These values indicate that the differences between the observed (actual) and frontier (potential) output are due to inefficiency and not chance alone. The estimate of γ (the ratio of the variance of district specific TE to the total variance of output) is 0.4, indicating that 40 per cent of the difference between the observed and frontier output are primarily due to factors which are under the control of farms in districts.

(ii) Estimates of Technical Efficiency

We find the mean technical efficiency in the sample to be roughly 79 per cent, which means that the sample districts, on average, could increase their agricultural output by 21 per cent without additional resources through proper (i.e., more efficient) use of existing inputs and technology. Put differently, on average roughly 21 per cent of the technical potential of districts was not realized in raising agriculture. In the last Column of Table 4, we present state-wise mean values of technical efficiencies. The mean TE does not vary drastically among states. We find the most efficient states to be Tamil Nadu, Punjab, and – quite surprisingly - Orissa.

Table 4

Distribution of the Sample Districts by Level of Technical Efficiency

State	Below 70%	70-75%	75-80%	80-85%	85-90%	Above 90%	Total	Mean TE (%)
Andhra Pradesh	0 (0)	2 (11)	6 (32)	9 (47)	2 (11)	0 (0)	19	80.66
Gujarat	0 (0)	1 (6)	6 (38)	7 (44)	2 (13)	0 (0)	16	80.85
Haryana	0 (0)	1 (20)	1 (20)	3 (60)	0 (0)	0 (0)	5	79.93
Karnataka	0 (0)	2 (12)	6 (35)	7 (41)	0 (0)	2 (12)	17	81.32
Maharashtra	0 (0)	2 (8)	15 (63)	7 (29)	0 (0)	0 (0)	24	78.07
Madhya Pradesh	4 (10)	6 (15)	17 (41)	12(29)	2 (5)	0 (0)	41	77.07
Orissa	0 (0)	0 (0)	0 (0)	6 (50)	6 (50)	0 (0)	12	84.95
Punjab	0 (0)	0 (0)	0 (0)	7 (64)	4 (36)	0 (0)	11	83.45
Rajasthan	4 (15)	1 (4)	7 (27)	13(50)	1 (4)	0 (0)	26	77.46
Tamil Nadu	1 (8)	0 (0)	1 (8)	4 (33)	5 (42)	1 (8)	12	83.45
Uttar Pradesh	6 (11)	7 (13)	25 (46)	12(22)	4 (7)	0 (0)	54	77.27
West Bengal	0 (0)	0 (0)	2 (18)	7 (64)	2 (18)	0 (0)	11	82.23
All-India	15 (6)	22 (9)	86 (35)	94 (38)	28 (11)	3 (1)	248	79.32

- Figures in parenthesis are rounded percentages with respect to the state total.

Intrastate differentials in TE show much greater variation (see Appendix 1). Across the entire sample, TE ranges from a low value of 41.69 per cent (Jaisalmer in Rajasthan) to 92.67 per cent (Kodagu in Karnataka). In Table 4, we also provide distributions of sample districts by level of TE value in various states. The poorest states – Madhya Pradesh, Uttar Pradesh, and Rajasthan - tend to have the most districts centered below the mean TE value. These poorer states have generally the most to gain from more efficient use of existing inputs. Orissa, once again, is the exception to this.

Given the low levels of human development in the state (see below), how is it possible that technical efficiency in Orissa is so high and evenly distributed across all districts? We propose and test for two possible explanations. First, Orissa, as a whole, ranks fourth among Indian states with respect to cropping intensity (gross cropped area divided by net sown area) and the proportion of food crops raised. Regarding the former, because of the lack of data, we are unable to control for cropping intensity at the district level. However, information is available at the state-level. Regarding the latter, we use both the aggregated and disaggregated agro-climatic zone measures.

The empirical test of these theories consists of estimating equation (6) but adding a dummy variable for district membership in Orissa. If our proposed explanations for Orissa's efficient production hold true, we would expect the addition of cropping intensity and/or agro-climatic variables to destroy the statistical and practical significance of the coefficient on the Orissa dummy variable. We find that agro-climatic zone membership passes the test, but cropping intensity, at least at the state-level, does not (results not shown).[14]

(iii) The Determinants of Technical Efficiency

Before we present the regression estimates of the determinants of technical efficiency, it might be illustrative to first look at the data differently. In Table 5, we divide the districts into groups by technical efficiency and present mean values of each of the socioeconomic variables by group. In general, more efficient districts appear to have higher literacy rates, lower infant mortality rates, and better road infrastructure; it is difficult to spot a trend with respect to average size of land holding and rural electrification. We also see that more efficient districts are general rice plurality districts, while less efficient districts are more likely to be wheat plurality districts.

Table 5

Socioeconomic Characteristics of Technical Efficiency Groups

TE Group	Literacy Rate	IMR	Pucca Road	Electrified Villages	Holding Size	Rice	Wheat
Below 70%	39.60	92.0	35.91	43.82	3.54	13.33	40.00
70-75%	35.73	95.32	41.62	65.43	2.05	09.09	50.00
75-80%	41.47	87.72	44.35	67.89	2.34	22.99	27.60
80-85%	44.18	78.45	47.38	60.42	2.07	33.33	27.08
85-90%	45.35	79.61	50.33	51.33	2.19	46.43	25.00
Above 90%	72.87	40.67	89.93	80.99	1.52	100.00	0.00

Source: As in Table 2.

In Table 6, we present the regression estimates for model (6). Column 1 illustrates the estimates for the full set of districts. The coefficient on literacy is positive and significant at 5 per cent level; the coefficient on rural electrification is surprisingly negative and significant at 5 per cent; and road infrastructure shows to have a positive effect on technical efficiency, at 10 per cent level of significance. We suspect that the results for electrification, both here and in the other columns, might reflect the imperfect nature of the variable. In the exact sense, this variable represents the percentage of villages electrified within a district. It does not say anything, however, about how this infrastructure might be used in agricultural production.

In columns 2 and 3, we show results for the agro-climatic subgroups semiarid and subhumid (as the F statistic on regressions for the other groups was insignificant). Clearly, there are differences in the determinants of technical efficiency across these two groups. In semiarid districts, IMR and road infrastructure have significant effects, in the expected direction, on technical efficiency. In these same districts, larger land holding sizes seem to improve efficiency. In subhumid districts, the coefficient on literacy is positive and significant at 10 per cent level and road has a significantly positive effect at 1 per cent level.

Table 6

Determinants of Technical Efficiency

Variables	Total	Semi-arid	Sub-humid	Rice	Wheat	Irrigated	Non-Irrigated
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	1.476 (8.20)	1.497 (6.56)	1.647 (5.51)	0.967 (3.44)	2.071 (6.34)	1.440 (6.71)	1.670 (5.09)
LITERACY	0.005 (2.39)	0.002 (0.71)	0.007 (1.85)	0.011 (3.37)	-0.001 (0.19)	0.006 (2.20)	0.004 (1.00)
IMR	-0.002 (1.62)	-0.004 (3.05)	-0.001 (0.63)	0.001 (0.65)	-0.007 (3.53)	-0.003 (2.28)	-0.001 (0.68)
PUCCA ROAD	0.002 (1.86)	0.005 (3.53)	0.002 (3.53)	0.008 (2.63)	-0.001 (0.56)	0.002 (1.028)	0.001 (0.479)
ELECTRIFIED VILLAGES	-0.003 (2.23)	-0.003 (1.46)	-0.008 (3.07)	-0.007 (3.01)	-0.004 (1.42)	-0.003 (1.39)	-0.004 (1.98)
HOLDING SIZE	-0.016 (1.46)	0.044 (1.96)	0.055 (1.46)	0.131 (2.46)	0.114 (3.90)	0.043 (1.863)	-0.032 (2.45)
R^2	0.116	0.317	0.141	0.286	0.361	0.175	0.130
N	248	117	85	69	74	135	113

-Figures in parenthesis are absolute t values

The relative importance of the socioeconomic explanatory variables also differs by crop plurality group. Rice plurality districts (column 4) seem to increase efficiency with improvements in literacy and road infrastructure, and larger average land holding sizes. In wheat districts (column 5), as expected, IMR has a negative and significant impact on technical efficiency. Interestingly the land holding shows has a positive and significant coefficient in both columns 4-5, reflecting the scale economies.

In the final two columns, we provide estimates for irrigated and non-irrigated districts. Literacy and IMR are both significant and show the expected signs for irrigated districts, and are both insignificant in the non-irrigated districts. It seems reasonable that districts employing irrigation technology achieve greater efficiency returns from education/ health than those do not. Additionally, we find that while efficiency increases with land holding size (significant at the 10% level) in irrigated districts, the exact opposite is true in non-irrigated districts. This can perhaps be explained by the fact that, in irrigated districts, firms are able to extend production effectively to larger parcels of land because water is less of a constraint. In non-irrigated districts, firms are constrained with respect to water, and thus may not be able to operate larger parcels of land as efficiently.

As a summary, we would like to point out that there are three messages to take from this analysis. First, better health, education, and road infrastructure can make firms or districts more efficient in their production activities. Second, what specifically drives technical (in)efficiency in a given set of districts depends on various regional and production characteristics such as irrigation technology, crop mix, and agro-climatic zone. Third, our models only explain roughly 10-35 per cent of variation in technical efficiency across districts; there is a great deal more to the technical efficiency story that, due to data limitations, is left unexplored in this study.

6. Concluding Remarks and Policy Implications

In this study, we have analyzed district level technical efficiency and its determinants for 1990-91. Using the stochastic frontier production approach, we have found that Indian districts have a mean technical efficiency of 79 percent, indicating that, on average, agricultural output can be increased by about 21 per cent with existing resources. In nearly half of the sample districts (123 out of 248), TE values lie below 80 percent. Of this set, 84 districts are spread across four states: Uttar Pradesh (38), Madhya Pradesh (27), and Maharashtra (17) and Rajasthan (12). These states stand to gain the most from policy interventions towards improving technical efficiency.

We have shown that health, education, and infrastructure can be powerful drivers of efficiency at the district level. Our findings with respect to health are in line with the burgeoning literature, which suggests that health can act as a strong engine for economic growth and poverty reduction. Being the first study (to our knowledge) that studies the macroeconomic impact of health in the context of Indian agriculture, we believe that future studies would be wise to account for this variable.

We also have shown that the relative importance of the determinants of technical efficiency across districts depends greatly on environmental factors, such as agro-climatic zones, technological factors (such as irrigation regime), and crop mix. The policy implications are clear: interventions to improve technical efficiency are not "one-size-fits-all." Indeed, even districts within the same state would benefit differently from the same set of interventions. In that sense, it might be wise to develop policy interventions at a more localized level.

Essentially, our results and discussion outline a quite ambitious research agenda for the future. While the technical efficiency literature has offered insight into the relative performance of firms or regions with respect meeting their potential, it is less clear how this information should/can be translated into policy prescriptions. There is certainly a need for increased data collection, so as to expand the analysis of potential determinants of efficiency. Also, as mentioned above, our results indicate the need to carefully incorporate into econometric models how the causes of inefficiency may vary across regions with different environmental and technological characteristics.

Finally, certain limitations of this study should be kept in mind. The major issue here is that the firm level efficiency concept has been applied to district level data, and that we use data aggregated across all crops. Nevertheless, the present results can be interpreted as indicative aggregative efficiency measures of all farms within the concerned districts. Moreover, we feel that aggregate-level studies, such as ours, can greatly complement firm level studies in the construction of appropriate efficiency generating policies.

Appendix I District Specific TE Values

Districts	TE	Districts	TE	Districts	TE	Districts	TE	Districts	TE
Andhra Pradesh		Gulbarga	81	Mandla	82.5	Barmer	84.1	Deoria	80.4
Adilabad	72.2	Hassan	75.2	Mandsaur	77.2	Bharatpur	83.8	Etah	77.5
Anantapur	84.2	Kodagu	92.7	Morena	82.5	Bhilwara	80.8	Etawah	77.3
Chitoor	83.8	Kolar	73.5	N'Simhapur	84.4	Bikaner	67	Faizabad	76.1
Cuddapah	81.5	Mandhya	81.7	Panna	81.4	Bundi	83.5	Farrukabad	79.5
East Godar	87.8	Mysore	84.7	Raigarh	75.8	Chittaurg	83	Fatepur	77
Guntur	79.1	Raichur	78.2	Raipur	79.7	Churu	81.3	Garhwal	82.4
Karimnagar	79.3	Shimboga	84.6	Raisen	84	Dungarpur	78.7	Ghazipur	69.9
Khammam	80.6	Tumkur	80.6	Rajgarh	65.8	Ganganagar	88	Gonda	78.1
Krishna	80.1	***Mean TE***	***81.3***	Ratlam	72.6	Jaipur	83.9	Gurakhpur	58.2
Kurnool	82	***Maharastra***		Rewa	67	Jaisalmer	41.7	Hamirpur	80.7
Mahbubnagar	74.2	Ahmadnagar	77.3	Sagar	78.5	Jalor	81.3	Hardoi	77.6
Medak	76.9	Akola	76.3	Satna	73	Jhalawar	79	Jalaun	58.3
Nalgonda	78.8	Amravati	78	Sehore	81.5	Jhunjhunun	65.4	Jaunpur	75.4
Nellore	80.5	Aurangabad	79.8	Seoni	83.3	Jodhpur	75	Jhansi	78.2
Nizambad	79.8	Bhandara	76.4	Shahdol	80.6	Kota	82	Kheri	82.8
Srikakulam	86.8	Bid	77.6	Shajapur	75.9	Nagaur	82.1	Lalitpur	75.6
Vizag	84.7	Buldana	76.3	Shivpuri	72.8	Pali	77.5	Lucknow	68
West Godar	83.7	Chandrapur	78.5	Sidhi	76.6	S. Madhopur	82.6	Mainpuri	71
Warangal	76.6	Dhule	73.7	Surguru	81	Sikar	72.7	Mathura	79.7
Mean TE	***80.7***	Jalgaon	81.1	Tikamgam	70.7	Sirohi	80.4	Meerut	83.8
Gujarat		Kolhapur	81.7	Ujjain	76.2	Tonk	78.6	Mirzapur	76.6
Ahmadabad	75.1	Nagpur	76.4	Vidisha	83.1	Udaipur	62.5	Moradab	80.7
Amreli	85.5	Nanded	75.3	***Mean TE***	***77.1***	***Mean TE***	***77.5***	Muzzafarn	83.6
Banas Kantha	77.7	Nashik	77.5	***Orissa***		***Tamil Nadu***		Nainital	82.7
Bharuch	83.8	Osman	80.9	Balangir	85.4	ChengaiMGR	84.4	Pilibit	79.3
Bhavnagar	82	Parbhani	81	Baleshwar	82.1	Coimbatore	89.7	Pithoragarh	88.7
Jamnagar	84.5	Pune	77.1	Cuttack	85.2	Kanyakumari	91.4	Pratapg	69.8
Junagadh	88.3	Raigarh	82.6	Dhenkanal	86.7	Madurai	85.4	Rae Boreli	72.1
Kachchh	83.7	Ratnagiri	81.8	Ganjam	84.6	North Arcot	84.1	Rampur	79.4
Kheda	76.8	Sangli	77.4	Kalahandi	86.4	Nilgiris	66.6	Saharanpur	78.1
Mahesana	78.9	Satara	80.1	Kendujhar	84.7	Ramnad	76.1	Shahjahanp	80.1
Panch Mahals	74.4	Thane	74.3	Mayurb	84.7	South Arcot	85.8	Sitapur	76.3
Rajkot	82.9	Wardha	75.5	Phulanbani	88.6	Salem	86.6	Sultanpur	76.3
Sabar Kantha	75.8	Yavatmal	77.4	Puri	86.3	Thanjavur	85.7	Tehri Garh	81.2
Surat	83.7	***Mean TE***	*78.1*	Sambalpur	82.3	Tirunelveli	84.1	Unnao	73.4
Surendranagar	81.1	***Madhya Pradesh***		Sundargarh	82.4	Tiruchy	81.5	Uttarkashi	86.4
Vadodara	79.4	Balaghat	78.9	***Mean TE***	***85***	***Mean TE***	***83.4***	Varanasi	72.1
Mean TE	***80.9***	Bastar	86.2	***Punjab***		***Utter Pradesh***		***Mean TE***	***77.3***
Haryana		Betul	80.3	Amritsar	82.1	Agra	76.9	***West Bengal***	
Ambala	74.3	Bhind	78.7	Bhatinda	85	Aligarh	76.8	Bankura	82.2
Gurgaon	81.1	Bhopal	75.9	Firozpur	85	Allahabad	71.4	Birbhum	83.3
Hisar	83.9	Bilaspur	79.7	Gurdasp	80.3	Almora	82.5	Darjiling	80
Jind	82.7	Chhatarpur	75.6	Hoshiarpur	82.4	Azamgarh	75.7	Haora	77.1
Karnal	77.7	Chhindwara	86.9	Jalandh.	84.5	Bahraich	74.4	Hugli	81
Mean TE	***79.9***	Datia	79.1	Kapurthala	83.4	Ballia	73.2	Jalpaig	82.3
Karnataka		Dewas	78	Ludhiana	83.5	Banda	79.9	Koch Bih	87.4
Belgaum	83.5	Dhar	75.1	Patiala	85.1	Bara Banki	76.4	Maldah	76.1
Bellary	74.8	Durg	60.8	Rupnagar	80.7	Bareilly	79.8	Medinipur	84.7
Bidar	79.2	Guna	74.2	Sangrur	86.3	Basti	69.6	Murshid	86.3
Bijapur	79.2	Gwalior	75.5	***Mean TE***	***83.4***	Bijnor	86.6	Nadia	84.2
Chikmag	78.1	Hoshangabad	80.2	***Rajasthan***		Budaun	76.9	*Mean TE*	*82.2*
Chitradurg	84.2	Indore	79.7	Ajmer	75.7	Bulandshahr	79.9		
DakshinKanad	91.4	Jabalpur	56.6	Alwar	84.6	Chamoli	87		
Dharwad	79.8	Jhabua	72.4	Banswara	78.8	Dehra Dun	81.5		

Notes

1. Source: FAO STATS on the Internet site of the Food and Agriculture Organization.

2. Vaidyanathan (1994) cautioned that urgent attention should be paid to technological innovation and to removing non-price and institutional constraints, which do not permit the full exploitation of the chosen technology at the farm level.

3. There are precedents for this. For example, Kalirajan and Shand (1997) consider state as the producing unit to examine the sources of output growth during 1980 to 1990.

4. Our choice of the district as the unit was partially determined by our desire to include health in the model. Farm level health data (typically, some anthropometric measure such as BMI or a measure of morbidity) is extremely difficult to find and collate. District level measures of infant/child mortality (a proxy for health) are readily available.

5. In these studies, either health (IMR) is not significant on its own, or is found to have a large effect, but in the context of an aggregate infrastructure quality measure.

6. Typically, health is used as a "conditioning" variable in Barro-type regressions, which estimate neoclassical growth models. In production functions studies, health is used as an input. Bloom *et al.* (2001) suggest that in both cases health is not specified in the manner, which fully captures its effect as a productivity-enhancing factor. This makes the coefficient on the health variable hard to

interpret, as one still does not know through what factors, and to what extent through these factors, health has its large effect. Bloom *et al.* get around this problem by constructing an "aggregate Mincer" equation, which specifies health as a labour augmenting factor. The same argument can be applied to the specification of education as well.

7. Mitra *et al. (*2002) consider health as an input to total factor productivity and technical efficiency in the context of Indian industries. However, the health variable (infant mortality rate) is made part of a larger index via PCA. Decomposition of the index shows large elasticities with respect to health.

8. This measure allows us to compare efficiency across similar economic units such as firms and aggregation of firms, for example at industry level or geographically (Kalirajan and Shand, 1994).

9. Since there is no logic behind this strong assumption, the newly developed "random coefficients approach" criticized this point (see Kalirajan and Shand, 1994).

10. In the initial estimation, we had included tractor and cattle population variables (which we got from the ICRISAT CD-ROM. Since the data was not available for the exact year in question, but for some of the surrounding years (say, 1987 and 1992). While animal labour seemed to remain relatively constant over time, the tractor variable, used in some of the initial estimates, did not. Therefore, we interpolated the values for 1990-91. Since the coefficients of these variables turned out to be negative/insignificant, we excluded them in the final analysis. We should also point out here that, due to the dearth of data available at the district level, we were unable to include other variables, such as overhead expenditure.

11. Most of these variables were given in per hectare, or per capita terms. We converted these into totals accordingly. Land area employed was calculated by multiplying the percentage of gross sown area by the total land area. Labour force size was determined using the percentage of agricultural workers (cultivators & labourers) in total population.

12. IMR and literacy rate are social indicators. IMR is used in many cross-sectional macro studies as an indicator of health status. In fact, all of the studies looking at health and economic performance in India (cited above) use this measure as a proxy for health status. Clearly, IMR reflects the quality of living conditions and availability of medical care in a region.

13. We use the LIMDEP (version 7.0) computer package to estimate equation (5). While this package does not give the estimates of TE values directly, we can obtain these via a few matrix comments.

14. It is noted that the sample includes only less than 50 per cent of total districts in Orissa. Further permanent land settlement in Orissa may be one of the reasons for higher efficiency.

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