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Stochastic Varying Coefficient Frontier Model in the Estimation of Technical Efficiency and Input Specific Technical Efficiency of Irrigated Agriculture in Tunisia

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Abstract: In this study, we propose a hybrid of a stochastic frontier regression. The proposed model and estimation differ from the conventional model of Aigner, Lovell and Schmidt. The model combines a stochastic frontier regression and a random coefficient regression: (a Stochastic Varying Coefficient Frontier Model) (SVCF) to estimate Technical Efficiency (TE) and Single Factor Specific Technical Efficiency (SFTE) of Tunisian farmers for irrigated crops such as: vegetable farming cereal and fruit-trees. The proposed single factor measure of efficiency is based on Kopp's notion of non-radial technical efficiency and it is shown that in the context of the SVCF model could provide firm-specific estimates even with inflexible production frontiers, such as the Cobb-Douglas. The empirical results indicate that the mean value of technical efficiency for all farms is estimated to be 54.7% for vegetable farming, 67.2% for cereal and 71.2% for fruit-trees. Input specific technical efficiency of irrigated water is under 40% for all crops.

Key words: SVCF, technical efficiency, single factor, irrigated crop, emprical result, Tunisia

INTRODUCTION

The role that the agricultural sector plays in the economy of developed countries has been recognised for many years. The main challenge of policy makers in these areas is how to attain food self-sufficiency by promoting output growth. Irrigation is one of the main important technologies of improving farm output and income. However, water resource scarcity continues to characterise water demand and supply for Tunisia's increasing economic and political pressure for water policy reform.

Agriculture by far the largest user of water, accounts for roughly 80% of consumptive use. Further, the application of highly subsidised associated inputs such as water has drained high cost policies and attention has turned towards better usage of the existing irrigation infrastructure and improving water conservation. Water resources in Tunisia come from rain and underground water reserves. Rain is very variable across regions, seasons and years. Neglecting the salinity factor leads to consider that the North of the country possess most water resources (60%) while the centre and the South have respectively, 17 and 23% of them. From these potential resources, the Ministry of Agriculture assesses that about 88%, i.e., 3,995 Mm^3 are immediately exploitable. From this volume, 76%, amounting to 3,043 Mm^3 are already developed. Water demand in Tunisia has steadily risen during the last 15 years. The irrigated area has more than doubled. The actual use of water considerably fluctuates across years depending on the needs of agriculture. In part because of this uncertainty, the present water pricing system is far from reflecting the economic value of irrigation water. The official price of water (between 0.032 and 0.06 TD m^{-3}) corresponds to the average cost with integral coverage of exploitation costs and partial reimbursement of investment.

However, the contribution of peasants to investment cost is rarely perceived. Similarly, the rental charges that are carried forward only cover from 15-60% of the exploitation costs. The deficit is filled with public subsidies. The variability of unit cost mostly results from the low irrigation intensity in some regions. Irrigation efficiency as a standard engineering measure has been traditionally used to assess water use management in the MENA region. Water use efficiency as applied in production economics theory, however has received less attention. To the knowledge in the MENA region, the only study which focus as on water performance measures using the production economics theory, concerns 11 individual farms producing spring tomatoes under drip irrigation in the Battinah region of the Sultanate of Oman (Omezzine and Zaibet, 1998). This study fills this gap with a case study of Tunisia. The measurement of water specific technical efficiency of Tunisian farmers for irrigated crops can provide useful insights into their potential for enhancing farm output and improving water resource use.

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MATERIALS AND METHODS

Theoretical framework: In an output oriented manner, technical efficiency is measured as a ratio of realized output to the potential output. The reliability of this measure of technical efficiency depends on how accurately the potential output is measured. It is in general assumed that the potential output is obtained by following the best practice methods, given the technology. This implies in turn that the potential output is determined by the underlying production frontier, given the level of inputs. Since by definition, technical efficiency is the discrepancy of the actual (realized) output from the production frontier, its measurement cannot proceed without the estimation of the production frontier.

The estimated frontier depends on the assumptions about the nature and the determinants of best practice methods. The former is related to the question of whether the best practice is a realized method inherent in the data or it may not be realized yet. Consequently, the potential output used to measure technical efficiency may or may not be realized. Up to now in the efficiency measurement literature, all but Kalirajan and Obwona (1994a) have agreed that the frontier results from observed output levels, produced by the firms using the best practice methods. In contrast, Kalirajan and Obwona (1994a) suggested that the potential output need not necessarily be observed in the data at hand. They attempted to justify that by arguing that the best practice method varies from input to input and thus not every firm would be applying all input efficiency.

However, it seems more reasonable whatsoever to think of best practice as referring to the whole set of inputs used by a firm instead of each input separately.

On the other hand concerning the determinants of best practice methods, two alternative models have been developed which are referred to as neutral and non-neutral frontier models. The former assumes that technical efficiency is independent of the levels of input used but is dependent on the method of application of inputs. Thus, even for identical levels of the same inputs, output differs due to differences in the methods of application. In turn the effectiveness of the methods of application is determined by various organizational factors which are influenced by socioeconomic, demographic etc., characteristics that affect the managerial ability of firms. In such a case, the estimated frontier is modeled as a neutral shift of the traditional average production function.

In contrast, the non-neutral frontier model assumes that both the methods of application of inputs as well as the level of inputs (i.e., scale of operation) determine the potential output and thus, the estimated frontier is modeled as a non-neutral shift of the traditional average production function. The non-neutral shift is related to that firms may acquire more information, knowledge and experience with respect to one input's productivity than the other (Huang and Liu, 1994). Apparently, it seems intuitively more appealing to argue that technical efficiency stems from two sources: firm-specific intrinsic characteristics and input levels.

Two alternative approaches have been used to model non-neutral production frontiers. On the one hand, Kalirajan and Obwona (1994a) developed the Stochastic Varying Coefficient Frontier (SVCF) model that related the notion of the non-neutral frontier with cross-sectional and possibly temporal variation in production response coefficients which include not only the intercept term as in the traditional frontier framework but also the slope coefficients. The idea of slope varying coefficients is consistent with the methods of application of inputs to depend on the level of inputs.

On the other hand, Huang and Liu (1994) accommodated the notion of the non-neutral frontier by modeling the one-sided error term measuring technical efficiency as a function of not only the variables affecting the managerial and organizational ability of firms but also of input levels, including interaction terms between them. Besides conceptual differences, these two non-neutral frontier models require quite different econometric estimation techniques.

In particular, Huang and Liu (1994)'s model is estimated with maximum likelihood which necessitate the imposition of particular distributional assumptions regarding the one-sided error term. In contrast, the SVCF model dispenses with this assumption as it can be estimated with generalized least squares by using Hildreth and Houck (1968)'s random coefficient regression procedure but the additive error term (appended to account for statistical noise) cannot be distinguished from the randomly varying intercept when only cross-section data are available (Kalirajan and Obwona, 1994b; Tsionas, 2002). Thus in a cross-sectional, setting, SVCF is deterministic frontier model. This is not true, however with panel data as it is possible to have a (cross-sectional) random intercept and noise at the same time (Kalirajan *et al*., 1996; Tsionas, 2002).

Despite its attractiveness as a non-neutral frontier model, SVCF's assumptions about the nature of best practice methods raise doubts about the reliability of the resulting efficiency measures. In particular, it is shown that as long as the best response coefficients are coming from different firms in the sample which as noted by

Kalirajan and Obwona (1994a) is quite likely to happen in empirical applications, the resulting frontier is not well defined in theoretical grounds and infeasible for any sample participant. Consequently by using it to compute, the maximum attainable output yields misleading results regarding both the magnitude of technical efficiency and the ranking of firms according to their efficiency scores. Moreover, Kalirajan and Obwona (1994a) measure of single factor technical efficiency (defined as the ratio of the actual to the maximum response coefficient for each input) also raises concerns about its appropriateness as an efficiency measure.

Measuring technical efficiency and input single factor technical efficiency in the stochastic varying coefficient frontier model: The first concern throughout this study is to estimate production frontiers of farmers in irrigated agriculture using micro-data from the Tunisian national farm irrigation survey. We emphasize the empirical use of random coefficient models when analysing the individual farm technical efficiency.

The production frontier approach is used to investigate farm technical efficiency. It refers to farmer's ability to produce the maximum possible output from a given set of inputs and technology. Many empirical studies have so far investigated the pattern and source of farm technical efficiency in developed countries. A few analyses, however have focused on the economic inefficiency in irrigated crops using water resource as input in the production frontier. A previous study developed by McGuckin *et al.* (1992) provided partial results since, it accounted only for water in the technology process and excluded other production inputs.

The economic implications of this finding are limited, especially when we aim to stress the importance of examining water substitution in production relationships and to seek the possibilities of adjusting the techniques in farm irrigation practices to accommodate changing scarcities of water. In many applications, technical efficiency is estimated using the stochastic frontier production function. The main assumption is that the frontier production function is a neutral shift of the conventional production function. This may be restrictive especially if we allow for heterogeneity among the farmers' production process in using their inputs.

In a recent study, Croppenstedt and Demeke (1997) has shown how efficiency measures could be derived from a random coefficient production model. This approach has the advantage of relaxing the traditional assumption of a neutral-shift of the frontier from the conventional production function. Besides, estimates of input-specific technical efficiency can be computed without imposing the restrictive assumption that specific technical efficiencies depend on the levels of the inputs used. Hence, let us suppose that the production technology of farmers is expressed as a Cobb-Douglas production function, such as:

$$\ln(y_i) = \beta_{0i} + \sum_{k=1}^{K} \beta_{ik} \ln(x_{ik}) + \varepsilon_i \qquad (1)$$

Where:

- y_i = The output of the ith farm
- x_i = A vector conditioning factor that affect production
- β_i = a K vector of unknown parameter for each unit I
- ε_i = Assumed to be independent and identically distributed as N (0, σ^2)

We use the Swamy (1971) random coefficient approach which assumes that each farm parameter vector β_i varies from the mean response by a vector of random errors μ_i that is:

$$\beta_{ik} = \beta_k + \mu_{ik} \qquad (2)$$

Substituting Eq. 2 and 1 gives:

$$\ln(y_i) = \beta_0 + \mu_{i0} + \sum_{k=1}^{K} (\beta_k + \mu_{ik}) \ln(x_{ik}) + \varepsilon_i \qquad (3)$$

$$\ln(y_i) = \beta_0 + \sum_{k=1}^{K} \beta_k \ln(x_{ik}) + \mu_{i0} + \sum_{k=1}^{K} \mu_{ik} \ln(x_{ik}) + \varepsilon_i \qquad (4)$$

$$\ln(y_i) = \beta_0 + \sum_{k=1}^{K} \beta_k \ln(x_{ik}) + w_i \qquad (5)$$

$$y_i = X_i'\beta + w_i \qquad (6)$$

Where:

$$w_i = X_i'\mu_i + \varepsilon_i$$

Further, we assume that: $\mu_i \sim N(0, \Omega)$ with $\Omega = \text{diag}(1, \sigma_1^2, \sigma_2^2, \sigma_k^2$. So that we have:

$$V(w_i) = \sigma^2 + X_i'\Omega X_i \qquad (7)$$

So, Eq. 3 can be written more compactly, for all the n observations as:

$$Y = X\beta + W \qquad (8)$$

where, X is an NxK matrix of stacked X_i' and Y, β and W are vectors of order N, K and N, respectively. A GLS estimate of the mean response β is given by:

$$\hat{\beta} = (X'\Sigma^{-1}X)^{-1}X'\Sigma^{-1}Y$$

Where:

$$\Sigma = E(ww') = D_x(I_N \otimes \Omega)D_x' + \sigma^2 I$$

$$D_x = diag(X_1' \cdots X_k')$$

Since, variances σ^2 and σ^2_k are not known, we adopt the Hildreth and Houck (1968) procedure. Let us write the parameter vector $\dot{\alpha}$ as:

$$\dot{\alpha} = (\sigma_1^2 ... \sigma_k^2)'$$

An unbiased estimator for σ^2 is given by:

$$\hat{\sigma}^2 = \frac{Y'MY}{n-k}$$

Since, we have:

$$E(\hat{w}_i^2) = \sum_{j=1}^{n}\sum_{k=1}^{K} m_{ij}^2 x_{ij}^2 \sigma_k^2$$

This can be written more compactly as:

$$E(\dot{\hat{W}}) = \dot{M}\dot{X}\dot{\alpha}$$

Where:

$$M = \left[m_{ij}\right] = I - X(X'X)^{-1}X'$$

and a dot indicates a vector (matrix) derived by squaring each element. Hence, an estimator of $\dot{\alpha}$ would be:

$$\hat{\dot{\alpha}} = (\dot{X}'\dot{M}^2\dot{X})^{-1}\dot{X}'\dot{M}\dot{\hat{W}}$$

After inserting the estimates of Ω and σ^2in Eq. 6, we obtain the feasible GLS estimator of β. Then, the individual estimates of the β_i 's are given by Griffiths (1972):

$$\hat{\beta}_i = \hat{\beta} + \hat{\Omega}X_i'(X_i\hat{\Omega}X_i')^{-1}(Y_i - X_i\hat{\beta}) \tag{9}$$

Having Eq. 1, Kalirajan and Obwona (1994a) followed the tradition of the frontier literature and measured output-oriented technical efficiency by the ratio of actual to potential output, i.e., TE =y/y*. However, in calculating the potential output that serves as a benchmark they used the maximum of the estimated values of the response coefficients for each input which are defined as:

$$\hat{\beta}_{ik}^* = \text{Max}\left\{\hat{\beta}_k + \hat{\mu}_{ik}\right\} \quad i=1...n \quad k=0,1,...K \tag{10}$$

Then, the frontier is given as:

$$\ln(y_i^*) = \beta_{0i}^* + \sum_{i=1}^{K} \beta_{ik}^* \ln(x_{ik}) \tag{11}$$

The idea behind this formulation is that both the intercept and the slope coefficients for those who are using the best practice methods would be larger than for those who are not following the best practice methods (Huang and Kalirajan, 1997).

There are two equally possible roots for the origin of the maximum response coefficients. On the one hand, it may be argued that not every firm would be applying all the inputs efficiently and thus, the maximum response coefficients need not come from a single firm. The main reason for this is that best practice methods vary from input to input. On the other hand, we may argue that a firm which uses same inputs efficiently may also use all inputs efficiently and thus the possibility that all maximum response coefficients may come from the same firm cannot be completely ruled out.

The implications of these two possibilities for the measurement of technical efficiency are very different. In the case where all maximum response coefficients are coming from the same firm, Eq. 2 represents an apparently well defined frontier and it can be used to provide reasonable estimates of technical efficiency as well as a consistent ranking of firms according to their efficiency scores.

However, when the maximum response coefficients are coming from different firms in the sample which as was noted by Kalirajan and Obwona (1994a) is quite likely to happen in empirical applications, two problems arise. First, the frontier described by might not be feasible for any sample participant, implying that none of the firms in the sample operates with full efficiency. It is obvious that when all best response coefficients are coming from the same firm, there is at least one firm in the sample that operates efficiently. If however, the best response coefficients are coming from different firms, none of the firms in the sample operates with full efficiency. This is a rather simply way to check the origin of the best response coefficients. For a deterministic frontier model, this contradicts with the cornerstone assumption in efficiency measurement literature, namely that efficiency is a relative concept measured with reference to observed best practice outcomes and a benchmark that is determined by some peer firms in the sample.

In a stochastic frontier model, it is quite likely that none of the firms in the sample operates with full efficiency but this is due to stochastic disturbances and not because the frontier is not feasible to sample participants. Second, the resulting frontier in may not be well defined in the sense that it violates certain theoretical properties. Consequently, the estimated technical efficiency scores are inconsistent. Even though, the aforementioned problems are not meet at the empirical results reported by Kalirajan and Obwona (1994a) and Salim and Kalirajan (1999) as the maximum response coefficients are coming for same firm, there are inherent in other studies. For the Kalirajan and Obwona (1994a) study in particular which reports estimates of the potential and actual output for each firm separately, it can be seen that the maximum response coefficients are from the firm with identification number 43. For example, Kalirajan and Obwona (1994b), Huang and Kalirajan (1997), Kaliajan and Huang (2001) as well as the present study, found that the maximum response coefficients are coming from different firms.

A different procedure for calculating technical inefficiency scores is proposed in this study to resolve the above shortcomings of the SVCF model which relies on the idea that best practice methods refer to the whole set of inputs used by a firm instead of each input separately. Starting with the basic relation that $y_i = f(.)\, TE_i$ where f (.) refers to the production frontier we can rewrite it for the Cobb-Douglass form as:

$$\ln(y_i) = \beta_0 + \sum_{k=1}^{K} \beta_k \ln(x_{ik}) + \ln TE_i \qquad (12)$$

On the other hand, by explicitly considering the random coefficient formulation of Eq. 4, it may be written as (Notice that this formulation is observationally equivalent to a (fixed coefficient) neutral frontier model with heteroscedastic statistical noise (Salim and Kalirajan, 1999; Tsionas, 2002) but it is estimated with a completely different method):

$$\ln(y_i) = \beta_0 + \sum_{k=1}^{K}\beta_k \ln(x_{ik}) + \mu_{i0} + \sum_{k=1}^{K}\mu_{ik} \ln(x_{ik}) \qquad (13)$$

Then by comparing Eq. 10 and 11 yields:

$$\ln TE_i = \mu_{i0} + \sum_{k=1}^{K} \mu_{ik} \ln(x_{ik}) \qquad (14)$$

Notice that Eq. 14 is completely analogous to the measure of technical efficiency used by Huang and Liu (1994) in the maximum likelihood formulation of the non-neutral frontier model. Given the assumptions about μ, it is clear that the expected value of $\ln TE_i$ in Eq. 14 is equal to zero implying that the expected value of TE_i is equal to one.

This means that the estimated values of TE may be less or greater than one. To ensure that estimated values of TE are bounded above by one, the following normalization suggested by Schmidt and Sickles (1984) is employed:

$$\ln TE_i = \max\left\{\hat{\mu}_{i0} + \sum_{i=1}^{K} \hat{\mu}_{ik} \ln(x_{ik})\right\} - \left(\hat{\mu}_{i0} + \sum_{i=1}^{K} \hat{\mu}_{ik} \ln(x_{ik})\right) \qquad (15)$$

Where ^ denotes estimates values. This normalization amounts to counting the most efficient firm in the sample as fully efficient and to compare efficiency across firms in a consistent manner. On the other hand, Kalirajan and Obwona (1994a, b) used the ratio of the actual to the maximum response coefficients for each input to obtain firm-specific estimates of input-specific technical efficiency. That is:

$$ITE_i^k = \frac{\beta_{ik}}{\max\{\beta_{ik}\}} \qquad (16)$$

Where values <1 indicate inefficiency. The inappropriateness of Eq. 16 as an efficiency measure arises from the fact that is based on production-elasticity which following Forsund (1996) are frontier measures. Thus, Eq. 16 lacks any theoretical foundation for being an appropriate efficiency measure. Instead Kopp (1981)'s notion of ITE_i^k may be used to identify in a theoretically consistent way the technical efficient use of individual inputs. In particular, Kopp (1981)'s measure of ITE_i^k is defined as the ratio of minimum feasible to observed use of each input conditional on the production technology and the observed levels of output and other inputs, i.e.,

$$ITE_i^k = \frac{x_{ik}^l}{x_{ik}} \qquad (17)$$

The minimum feasible use X_{ik} for the kth input coincides with that quantity necessary to ensure technical efficiency without altering the quantities of other inputs and the level of output produced. Then, it is clear that Kopp (1981)'s measure of ITE_i^k is non-radial and has an input-conserving orientation which however cannot be converted into a cost-saving measure. According to Reinhard *et al.* (1999), the minimum feasible use of the K input for the ith firm can be computed through the fitted frontier function assuming:

$$\ln(y_i) = \hat{\beta}_{0i} + \sum_{k=1}^{K-1}\hat{\beta}_k \ln(x_{ik}) + \hat{\beta}_k \ln(x_{ik}^l) \qquad (18)$$

Then, there are two alternatives: either we can solve Eq. 8 for In (x_{ik}) and then compute ITE_{ik} using the observed x_{ik} or we can combine Eq. 8, 3 and 5 to show that:

$$\ln ITE_i^k = \ln x_{ik}^1 - \ln x_{ik} = \frac{\ln TE_i}{\hat{\beta}_k} \quad (19)$$

Then by using again Schmidt and Sickles (1984) normalization, we can compute input-specific technical efficiencies as:

$$\ln ITE_i^k = \max\left\{\frac{\hat{\mu}_{i0} + \sum_{i=1}^{K} \hat{\mu}_{ik} \ln(x_{ik})}{\hat{\beta}_k}\right\} - \left(\frac{\hat{\mu}_{i0} + \sum_{i=1}^{K} \hat{\mu}_{ik} \ln(x_{ik})}{\hat{\beta}_k}\right) \quad (20)$$

This ensures that they lie in the interval.

RESULTS AND DISCUSSION

The data are taken from a national survey focusing of irrigated agriculture conducted by the Tunisian Ministry of Agriculture in 2006. The sampling scheme is stratified by zone (11 regions equally distributed on an East-West axis across the three agro-climatic region: North, Centre and South), irrigation source, perimeter size and perimeter age. About 250 agricultural producers have been surveyed, leaving 218 observations (Table 1) because of missing or erroneous data.

The objective of the survey was to gather basic data about producers, their production unit and the use of water. Since, the collection was organized around the different crops, we dispose of input and output information that is specific to three crops: fruit-trees, vegetable farming and cereal.

The main variables entering the stochastic varying coefficient frontier model are as follows (Table 2). Descriptive statistics for the sample of 218 households by crop are shown in Table 3. Data on each input and output were collected by crop. Inputs include the use of farmyard manure fertilizer, human labor, mechanic traction, animal traction irrigated water, in each quantity was recorded.

Parameter estimates of the Cobb-Douglas stochastic varying coefficient frontier model for irrigated crop growing farms in Tunisia are shown in Table 4. The hypothesis of random coefficient variation cannot be rejected by the Breusch-Pagan LM-test lending support to stochastic varying coefficient model. Indeed, individual response coefficients vary considerably among sample farms (Table 1) implying that farmers a re using quite different farming practices. Also, mean response coefficients along with the corresponding t-ratios and range of coefficient value are shown in Table 4. For all crop estimate of stochastic varying coefficient frontier model indicate that irrigated water exhibited the highest output elasticity (between 0.258-0.343 and significative at 10%) followed by land size (between 0.170 and 0.213). Mean estimate of returns to scale is found to be close to unity. The results in Table 4 shows that the maximum response coefficients are coming from the same farm in the sample (firm number 12 for vegetable farming, firm number 15 for cereal and firm number 13 for fruit tree). All this firm are localized in the north of Tunisia, Hence, the estimates of farm-specific technical efficiency using Kalirajan and Obwona (1994a)'s procedure may lead to meaningful results.

The results of technical efficiency estimate are shown in Table 5-7 in the form of frequency distribution within a quartiles range. The mean value of technical efficiency for all farms is estimated to be 54.7%, for vegetable farming with a range from 10.7-100 and 67.2% for cereal with a range from 16.8-100 and 71.2% for fruit-trees with a range from 27.2-100%.

This result indicates that output can be increased on average by 45.3% for vegetable farming, 32.8% for cereal and 28.8% for fruit-tree with the present state of technology and the same amount of inputs as before if the technical inefficiency is removed completely. Statistics indicate that 75.6% of the farmers are <50% efficiency for vegetable farming. Thus, there is considerable room for improvement in the technical

Table 1: Interviewed perimeters

Regions	Perimeter surveyed	No. of investigations
Ariana	El Battan, Sidi Naji	24
Bizerte	Mateur, Ghezala	13
Nabeul	Menzel Bouzelfa, Lebna	27
Ben Arous	Mornag	13
Jendouba	S.Esssebt, Bouhertma	19
Zagouane	Zagouane	15
Kairouan	Sidi Saad	11
	Hajeb	22
Mahdia	Bir Ben Kamla, Hiboun	14
Sousse	Chott Meriam, Sidi Bouali	20
Gabés	Metouia, Zerig, Ketana	21
Kebeli	Matrouha	19
Total	-	218

Table 2: Description of output, input and farm-specific variables

Variables name	Description
Output (Y)	Output for a particular crop (in ton)
Input variables	
Manure (X1)	Farmyard manure fertiliser, ton
Labor (X2)	Labor of farmer/family labor, regular and casual labor (in days)
Mechanization (X3)	Mechanic traction, hours
Animal traction(X4)	Animal traction, days
Irrigated water (X5)	Among of water applied, in m^3
Farm size (X6)	Total farm size, acres

Table 3: Summary statistics of output, input and farm-specific variables

	Fruit-tree				Vegetable farming				Cereal			
Veraiables name	Mean	S.D	Min	Max	Mean	S.D	Min	Max	Mean	S.D	Min	Max
Output(Y)	11.280	20.370	0.03	120.00	17.00	31.920	0.15	300	14.280	19.20	0.90	150
Input variables												
Manure (X1)	32.230	56.910	3.00	401.50	39.70	163.300	0.75	2007	13.540	14.80	0.40	72
Labor (X2)	86.470	154.400	25.00	980.00	88.60	129.600	250.00	1080	46.040	43.60	30.00	200
Mechanization (X3)	6.383	36.550	2.00	400.00	4.97	5.841	0.00	38	406.900	97.60	328.00	606
Animal traction(X4)	18.300	39.360	5.00	360.00	12.30	26.930	2.00	200	12.290	16.60	0.50	100
Irrigated water (X5)	4478.000	9382.000	200.00	32930.00	1815.00	2298.000	126.00	15000	5107.000	4509.00	1040.00	33300
Land size (X6)	1.682	2.266	0.05	18.00	1.02	1.282	0.05	10	2.486	2.28	0.03	12

Table 4: Estimates of stochastic varying coefficient frontier model

	Fruit-tree			Vegetable farming			Cereal		
Crop input	Coeff.	t.student	Range coeff.	Coeff.	t.student	Range coeff.	Coeff.	t.student	Range coeff.
Manure (X1)	0.092	1.010	0.055/0.174	0.129	1.700	0.012/0.178	0.1500	3.2200	0.137/0.564
Labor (X2)	0.158	2.410	0.0196/0.192	0.157	3.160	0.060/0.255	0.1700	0.3600	0.110/0.187
Mechanization (X3)	0.117	2.320	0.016/0.18	0.169	1.300	0.035/0.174	0.1670	0.8400	0.0589:0.225
Animal traction (X4)	0.134	0.550	0.101/0.180	0.160	3.310	0.065/0.255	0.1087	3.7000	0.081/0.136
Irrigated water (X5)	0.343	2.400	0.158/0.898	0.260	2.390	0.014/0.348	0.2580	3.6100	0.114/0.385
Farm size (X6)	0.213	1.320	0.13/0.530	0.170	1.670	0.082/1.954	0.1930	0.5400	0.024/0.435
Constant	1.704	7.730	0.113/1.727	0.308	0.940	0.033/0.453	0.9510	0.6500	0.666./3.333
RTS	-	1.057	-		1.045	- -		1.0467	- -
LM	-	616.580	-		239.360	- -		106.5200	- -
No.Obs	-	130.000	-		207.000	- -		67.0000	- -

Table 5: Frequency distributions of output and input specific technical efficiency estimates of fruit tree

		Input efficiency					
Efficiency index (%)	Output efficiency	X1	X2	X3	X4	X5	X6
<25	15.000	55.550	67.900	79.010	46.540	74.040	19.750
25-50	11.200	30.860	18.510	12.340	34.930	9.870	14.810
50-75	39.200	9.870	7.400	7.400	6.170	8.620	45.670
75-100	34.600	3.700	6.170	1.230	12.340	7.470	19.750
Mean	71.200	34.400	47.000	38.200	41.500	36.200	59.700
Minimum	27.200	1.000	1.300	0.500	1.200	0.700	1.700
Maximum	100.000	100.000	100.000	100.000	100.000	100.000	100.000
Standarddeviation	0.291	0.174	0.238	0.081	0.208	0.133	0.302

Table 6: Frequency distributions of output and input specific technical efficiency estimates of cereal

		Input efficiency					
Efficiency index (%)	Output efficiency	X1	X2	X3	X4	X5	X6
<25	11.400	20.750	14.140	27.900	33.450	71.040	15.640
25-50	28.000	12.810	59.740	48.610	42.860	20.320	55.930
50-75	30.900	40.670	19.730	17.400	20.770	8.520	18.270
75-100	29.700	28.750	6.370	6.270	2.700	0.120	10.340
Mean	67.200	52.540	67.000	58.320	59.060	38.170	68.230
Minimum	16.800	5.130	19.000	0.900	10.010	1.500	5.000
Maximum	100.000	100.000	100.000	100.000	100.000	100.000	100.000
Standarddeviation	0.162	0.210	0.270	0.230	0.240	0.360	0.160

Table 7: Frequency distributions of output and input specific technical efficiency estimates of vegetable farming

		Input efficiency					
Efficiency index (%)	Output efficiency	X1	X3	X2	X4	X5	X6
<25	9.400	38.210	29.250	27.300	28.040	70.010	22.170
25-50	66.200	47.500	50.110	48.300	60.900	14.090	45.130
50-75	20.400	13.190	12.350	23.200	8.060	10.900	27.250
75-100	4.000	1.100	9.290	1.200	2.000	5.100	5.450
Mean	54.700	41.000	44.400	56.200	47.000	36.000	59.700
Minimum	10.700	1.200	1.500	0.700	1.300	0.500	1.700
Maximum	100.000	100.000	100.000	100.000	100.000	100.000	100.000
Standard deviation	0.138	0.208	0.174	0.133	0.238	0.081	0.302

efficiency of this culture in Tunisian agriculture. However, cereal and fruit-trees have almost descriptive statistic for efficiency level. Over than 65% of the farmers have efficiency level under 75% (inefficiency at 25%). In summary, these statistics are quite comparable to those reported by previous frontier studies in agriculture in developing countries. For example, the overall average level of technical efficiency computed from all the studies presented by Thiam is 68%. The parametric studies relying on the Cobb-Douglas form reported technical efficiency measures ranging from 52-84%, with an average of 71%.

Estimates of input-specific technical efficiencies, obtained from Eq. 20, indicate that land is utilized more efficiently in the production process followed by labor, animal traction, mechanization and fertilizers. Further, all individual measures of input-specific technical efficiencies indicate a considerable variation among farms in the sample which is more intense in other intermediate inputs and fertilizers. The results are shown in Table 5-7 that irrigation water is a highly significant determinant of crop yield. The coefficient of irrigation water quantity is an elasticity measure. Input specific technical efficiency of irrigated water is under 40% for all crop. Clearly, there is a substantial scope for improving output even with the same level of inputs. On the input side, the results indicate that in using water, farmers operate close to the frontier of water use and that there is a limited potential to improve water-specific technical efficiency. The average technical efficiency for water use was about 36% for vegetable farming with a minimum under 1, 35.2% for fruit tree with a minimum under 2-38.17% for cereals. Further more for all crops >80% of the farmers are at efficiency level under 50%. The implication is that gains in water management can be achieved from improved use of water in potato production. This result suggests policy recommendations to make up for this inefficiency.

CONCLUSION

The stochastic varying coefficient model developed by Kalirajan and Obwona (1994a) have all interesting features of a non-neutral frontier model but their procedure for estimating both the output and the input-specific technical efficiency measures is not free of theoretical and methodological problems. Specifically, it has been shown that the frontier as defined by Kalirajan and Obwona (1994a) is in practice infeasible for any sample participant and theoretically improper whenever the maximum response coefficients are not coming from the same production unit. Consequently by using it to compute, the maximum attainable output yields misleading results regarding both the magnitude of technical efficiency and the ranking of firms according to their efficiency scores. The main reason behind these problems is Kalirajan and Obwona (1994a)'s assumption that the best practice methods refer to each input separately instead of the whole set of inputs used by a firm.

RECOMMENDATIONS

In order to overcome these problems, we suggest an alternative procedure for measuring output and input-specific technical efficiencies within the stochastic varying coefficient model. The proposed measures are respectively analogous to those used by Huang and Liu (1994) in the maximum likelihood formulation of the non-neutral frontier model and Kopp (1981)'s definition of single-factor efficiency measure. After these adjustments, the stochastic varying coefficient model may be seen as a promising alternative to Huang and Liu (1994) non-neutral frontier model.

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