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AGRICULTURAL CREDIT PROGRAMS AND PRODUCTION EFFICIENCY: AN ANALYSIS OF TRADITIONAL FARMING IN SOUTHEASTERN MINAS GERAIS, BRAZIL

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INTRODUCTION

Over the past two decades, one of the primary policy actions directed toward improving the productivity and incomes of traditional farmers in developing countries has been the provision of agricultural credit at subsidized rates of interest. The rationale behind such programs focuses on the belief that the main barrier preventing the transformation of traditional agricultural production technologies to more modern and productive technologies is the inability of farmers to purchase the necessary technology. In principle then, if funds are made available to facilitate the purchase of such modernized production inputs, the productivity, and hence incomes, of traditional farmers will improve and the journey toward more developed agricultural production processes will have begun.

There is a rather noticeable lack of consensus regarding the desirability and effectiveness of such credit programs (Adams, 1971). Perhaps the best known criticism of the effectiveness of providing credit to traditional farmers is attributed to Shultz (1964). The "poor but efficient" hypothesis states that the provision of agricultural credit will be ineffective in improving productivity and incomes since investment opportunities are limited. Traditional farmers are hypothesized to be efficient but faced with technological barriers that cannot be overcome by the mere influx of capital provided by credit programs alone.

Considerable research has been directed towards analyzing the effects of credit programs on capital formation, productivity and efficiency of traditional agriculture. Much of this research has been centered in Brazil, where extensive credit programs have been formulated and implemented (Araujo and Meyer, 1978). The results of this research have provided a diversity of conclusions as to the effect that credit policies have on the productivity and efficiency of traditional farming.

Rao (1970) analyzed the economics of credit in Brazil and concluded there was an underutilization of capital on small farms and that credit would relieve capital shortages and improve output. Nelson (1971) in analyzing farm level production in Ribeirao Preto, however, found that technological barriers were present which would prevent credit programs from having a significant impact on capital formation and incomes.

Considerably more agreement is found in analyses of the allocative efficiency of traditional farmers in Brazil. Garcia (1971) concluded that small farms in the state of Minas Gerais were allocatively inefficient demonstrating excessive labor usage. Similar conclusions regarding allocative efficiency were obtained by Graber (1976) and Teixeira (1976) in their farm level studies. In addition, Drummond (1972) found that small traditional farms and larger mechanized farms exhibited no substantial differences in the efficiency of resource utilization in Minas Gerais State.

These studies do not represent a comprehensive list of the research conducted on traditional agriculture and credit in Brazil. They do, however, exemplify the disparity of research results as to the effectiveness of agricultural credit policies. Also, they seem to provide evidence contrary to the belief that traditional farmers have little to gain from a reallocation of resources.

Steitieh (1971, p. 96) in studying traditional agriculture in Southern Brazil concluded, ". . . that increased investment in inputs (capital formation), such as mechanized equipment and fertilizer alone is not the answer to increasing crop production. Better management, information and utilization of resources are as important and should be equally emphasized if any benefit is to be expected from increasing expenditure on these inputs." The implication here, of course, is that while credit availability may afford traditional farmers the opportunity to invest in modernized inputs, there is no guarantee that these inputs will be used in such manner as to realize the full extent of output gains possible. Thus the notion of technical efficiency in production arises.

This paper provides an analysis of the effects of the PRODEMATA program on the technical and allocative efficiencies of farms in the Zona da Mata region of Brazil. In contrast to previous studies analyzing allocative efficiency by means of fitted "average" production functions, this analysis is conducted in terms of frontier production functions and Farrell efficiency measures.

The PRODEMATA program was initiated in 1976 in cooperation with the World Bank with the broad objectives of inducing agricultural development in the Zona da Mata. The major instruments to achieve this objective include: 1) provision of agricultural credit and technical services, including extension activities and the construction of research and demonstration facilities and 2) investments in health, sanitation and education.

The primary focus of this paper is on the first instrument of implementing the PRODEMATA program. Emphasis is especially directed towards the effectiveness of technical services and extension activities in improving the technical and allocative efficiencies of participating farms. It is found that while the program appears to have had little impact on the allocative efficiencies of farmers in the Zona da Mata, there appears to have been a rather substantial impact on technical efficiency. In addition, the improvements in technical efficiency appear quite uniform across differing farm sizes.

The plan of the paper is as follows. The first section discusses the measurement of technical and allocative efficiency using frontier specifications. The model is developed in the second section and the data utilized in estimation are discussed. Empirical results are presented in the third section. The final section presents a brief summary and conclusions.

MEASURING TECHNICAL AND ALLOCATIVE EFFICIENCY

Technical inefficiency results from the failure of the firm to produce the maximum output rate from a given set of inputs. The production frontier defines an upper bound on the output from any given set of inputs. Thus, measures of technical efficiency depend in some fashion on the relationship between observed output and the corresponding output obtained on the frontier.

Allocative inefficiency results from the failure of firm to equate marginal rates of substitution with input price ratios. Factors of production are utilized in inefficient proportions when exogenously given factor prices are considered. Measures of allocative inefficiency are independent of technical efficiency in the sense that a firm may simultaneously be technically inefficient and allocatively efficient

Since the seminal paper by Farrell (1957) a great deal of effort has been directed toward estimating frontier models of a production technology and obtaining efficiency measures. The types of models that have resulted have included non-parametric deterministic models (Farrell, 1957; Farrell and Fieldhouse, 1965), deterministic full frontier models (Aigner and Chu, 1968), stochastic full frontier models (Greene, 1980) and stochastic frontier models (Aigner et al 1977; Meeusen and Van Den Broeck, 1977; Lee and Tyler, 1978).

From these frontier models two basic types of technical efficiency measures have evolved.[1] Not surprisingly, the validity of each measure depends on certain technological and stochastic assumptions of the underlying frontier model.

The stochastic frontier formulations of Aigner et al., (1977) and others parameterizes the measure of technical efficiency in the stochastic specification of the model. The disturbance component of these frontiers is composed of a symmetric random variable which captures the effects of weather, luck and other factors outside the control of the economic agent and a one sided disturbance which measures technical efficiency. The mean of the one sided distribution (sometimes called the efficiency distribution) provides a measure of the average technical efficiency for firms in the sample.

The stochastic specification of these models is attractive in that it is closely tied to some of the concepts involving the stochastic specification of production functions developed by Marchak and Andrews (1944) and Zellner et al. (1966). However, it is not generally possible to decompose the estimated residuals into their individual component effects. Thus, measures of technical efficiency cannot be obtained for each observation in the sample. Rather, a single measure for the sample taken as a whole can be obtained.

In contrast to stochastic frontier specifications, full frontier specifications posit only a one sided disturbance. This specification carries with it the implication that all deviations from the frontier are attributable to technical inefficiency. While it may be questionable to attribute all sources of variation to technical inefficiency, there is a considerable payoff to be found in this assumption. Specifically, the use of Farrell efficiency measures is justified, permitting efficiency measures to be obtained at each sample point.

Farrell efficiency measures are defined by comparing input bundles along a given ray through the origin. Although these radial measures were originally considered only for the unit isoquant of a linear homogeneous technology they have recently been generalized to be applicable to very general technologies (Kopp, 1981).[2] Furthermore, these generalized Farrell measures may be equivalently computed from a dual cost function (Kopp and Diewert, 1982).

The radial nature of Farrell efficiency measures may be demonstrated by using Figure 1. Let I^0 denote the frontier isoquant corresponding to output Y^0, and X_a denote the inefficient input bundle that yields this level of output. Along the ray OX_a, the input bundle X_b represents a technically efficient input bundle as it is located on the frontier isoquant. The Farrell measure of technical efficiency (TE) is then given by $TE = \frac{||X_b||}{||X_a||}$.

The Farrell measure of allocative efficiency is also a radial measure. Given a set of input prices which define the isocost line PP, the Point X_e corresponds to the technically and allocatively efficient input bundle. The point X_c, although not technically feasible to produce Y^0, yields a cost (given factor prices implicit in PP) equal to the technically feasible point X_e. Thus, along the ray OX_a, the measure of allocative efficiency (AE) is defined by AE = $\frac{||X_c||}{||X_a||}$.

The cost aspect of the technically infeasible point X_c and its use in measuring allocative efficiency provides some impetus towards obtaining measures of TE and AE in terms of cost. Specifically, Kopp and Diewert (1982) have recently developed dual efficiency measures obtainable from the cost function. Let P denote the vector of input prices defining the isocost line PP. The cost incurred to produce Y^0 with the technically inefficient input X_a is given by $P \cdot X_a$. Similarly, the cost of producing Y^0 with the technically efficient set of inputs is $P \cdot X_b$. Technical efficiency is then measured by TE = $\frac{P \cdot X_b}{P \cdot X_a}$. The total cost at point X_c is $P \cdot X_c$ which is equal to the cost incurred using the technically and allocatively efficient input bundle X_e. Allocative efficiency is then defined by AE = $\frac{P \cdot X_c}{P \cdot X_b}$.

The dual nature of the various efficiency measures is found in the fact that $\frac{||X_b||}{||X_a||} = \frac{P \cdot X_b}{P \cdot X_a}$ and $\frac{||X_e||}{||X_b||} = \frac{P \cdot X_c}{P \cdot X_b}$. Thus, one can obtain equivalent measures of technical and allocative efficiency using either the frontier production function and associated first order conditions or the dual frontier cost function. This is convenient from both a theoretical and computational standpoint. Theoretically, one can specify a quite general cost function and obtain efficiency measures corresponding to the implied underlying technology. From a computational point of view, it is easier to obtain efficiency measures from the cost function. Thus, even if direct estimation of the frontier production function is undertaken, efficiency measures may be obtained from an analytically constructed cost function.[3]

The choice between full frontier and stochastic frontier models results in a tradeoff situation. While stochastic frontiers offer a perhaps more realistic disturbance specification, it comes at the cost of being able to estimate only a single measure of average technical efficiency over the sample. In contrast, full frontier specifications allow technical efficiency to be estimated for each data point and admit a direct dual measure of technical efficiency from the cost function. However, to obtain these measures, one must assume that all departures from the frontier captured by the disturbance are directly attributable to technical inefficiency.

As pointed out by Kopp and Diewert (1982, p. 501), in the final analysis, the choice of which specification to use rests with the analyst. In the ensuing analysis, the stochastic full frontier specification developed by Greene (1980) is utilized. Thus, Farrell efficiency measures of technical and allocative efficiency at each data point are obtainable.

THE MODEL AND DATA

In order to obtain estimates of technical and allocative efficiency, direct estimation of full frontier production functions was undertaken. The data utilized were drawn from a sample of 435 farm firms in the Zona da Mata region of Brazil for the 1981-82 crop season. These data on production inputs and outputs were collected as part of the PRODEMATA program by the Agricultural Economics Department of the Federal University of Vicosa.

The data were partitioned on the basis of participation in the PRODEMATA program. The nonparticipant group was composed of 253 farms that had never participated in the Prodemata program. The participant group was composed of observations on 182 farms that had participated in the PRODEMATA supervised credit program in at least one year.

For each of these groups a Cobb-Douglas production specification was utilized. The specification is admittedly restrictive in terms of the properties of the underlying production technology. However, as interest centers on efficiency measurement and not an analysis of the general structure of the underlying production technology, this specification provides an adequate representation of production in the Zona da Mata. Further, the self dual nature of the Cobb-Douglas production function and its cost function provides a computational advantage in obtaining estimates of technical and allocative efficiency.[4]

The production function for each group (j = P,NP) was defined by

$$\ln Y_i = \ln A + B_1 \ln T_i + B_2 \ln L_i + B_3 \ln M_i - U_i \quad i=1,\ldots,N_j \qquad (1)$$

where Y_i denotes output, T_i is land in production, L_i is a measure of labor, M_i denotes intermediate materials and U_i is the disturbance component. Output was measured as the gross value of output deflated by the index of prices received for the Minas Gerais state (FGV, 1982).[5] Land was measured in hectares of land utilized in agricultural production. Labor input was measured in terms of man-day equivalents. Intermediate materials were defined as the deflated value of expenditures on seed, fertilizers, pesticides, draft animal services and mechanized services. The deflator used was the index of prices paid for production items in the Minas Gerais state (FGV, 1982).

The disturbances are assumed to be independent and identically distributed as Gamma random variables with parameters λ and P. Given appropriate assumptions concerning the matrix of exogenous variables (see Greene, 1980, p. 31) the production function specification in equation (1) corresponds to a stochastic full frontier model. It should be noted that with the restrictions $\lambda>0$ and $P>2$, the model in equation (1) may be estimated via maximum liklihood as a regular case. This specification differs from other full frontier specifications that may be "estimated" by maximum liklihood in that the asymptotic sampling properties of the parameter estimates are known.[6]

Given the parameter estimates for the production function in equation (1), the dual cost function may be easily constructed as

$$C(Y,P) = k\, P_T^{\alpha_1}\, P_L^{\alpha_2}\, P_M^{\alpha_3}\, Y^r \tag{2}$$

where $\alpha_i = rb_i$, $= r = (\Sigma_i b_i)^{-1}$, $k = [\hat{A}\, \pi_i b_i^{\,b_i}]^{-\frac{1}{r}}$ and the b_i $i=1,\ldots,3$ are the estimated values of the B_i parameters from Equation (1). Following Kopp and Diewert (1982), the implied dual cost function may be used to estimate technical and allocative efficiency.

For ease of exposition, denote the set of fixed input prices the firm faces as $P' = (P_T, P_L, P_m)$ and define the observed output of the firm by Y_o. Finally, using Figure 1, define $X_j' = (T_j, L_j, M_j)$ $j = A,B,C$ as a vector of inputs. Thus, the observed set of inputs producing output Y_o with input prices P is denoted X_A.

The measure of technical efficiency for the input bundle X_A is given by $\frac{||\hat{X}_C||}{||X_A||} = \frac{P\cdot \hat{X}_C}{P\cdot X_A}$. Thus, the input set $\hat{X}_C$ must be determined. Since $\hat{X}_C$ lies at the intersection of the ray OX_A and the isocost line $\{X \mid P\cdot X = C(Y_o, P)\}$,[7] $\hat{X}_C$ may be determined from the expression

$$\hat{X}_C = \frac{C(Y_o, P)}{P\cdot X_A} \cdot X_A \tag{3}$$

Thus, the technical efficiency measure for X_A is given by $TE_A = \frac{C(Y_o, P)}{P \cdot X_A}$.

The estimate of allocative efficiency for X_A is defined by $\frac{||\hat{X}_B||}{||X_A||} = \frac{P \cdot \hat{X}_B}{P \cdot X_A}$. The determination of $\hat{X}_B$ is somewhat difficult since it is located at the intersection of the ray OX_A and the efficient isoquant (denoted I_0 in Figure 1). Since $\hat{X}_B$ is located on the ray OX_A, we know that $\hat{X}_B = \theta X_A$. Also since $\hat{X}_B$ is on the technically efficient isoquant, for some (unknown) set of input prices, say P_B, $\hat{X}_B$ will correspond to the allocatively efficient vector of inputs (i.e. $\hat{X}_B = \nabla_P C(Y_o, P_B)$). Thus, the determination of $\hat{X}_B$ involves the simultaneous solution of the equation system

$$\hat{X}_B = \theta X_A \tag{4}$$

$$\hat{X}_B = \nabla_P C(Y_o, P_B)$$

Note that, in the general case, this system of equations contains 2n equations in 2n + 1 unknowns $(\hat{X}_B, P_B, \theta)$.

For the problem at hand, this system of equations can be solved by using the normalization $P_m = 1$. Denoting the normalized prices of P_T and P_L by $\hat{P}_T \equiv \frac{P_T}{P_M}$ and $\hat{P}_L \equiv \frac{P_L}{P_M}$, the following equation system is obtained

$$\frac{L_B}{\hat{T}_B} = \frac{L_A}{T_A} \equiv k_{21} \tag{5.1}$$

$$\frac{\hat{M}_B}{\hat{T}_B} = \frac{M_A}{T_A} \equiv k_{31} \tag{5.2}$$

$$\hat{T}_B = \left(\frac{\alpha_1}{\hat{P}_L}\right) C(Y_o, \hat{P}_T, \hat{P}_L, 1) \tag{5.3}$$

$$\hat{L}_B = \left(\frac{\alpha_2}{\hat{P}_L}\right) C(Y_o, \hat{P}_T, \hat{P}_L, 1) \tag{5.4}$$

$$\hat{M}_B = \alpha_3\ C(Y_o, \hat{P}_T, \hat{P}_L, 1) \tag{5.5}$$

Solving these equations for the normalized prices, $\hat{P}_L$ and $\hat{P}_M$ yields

$$\hat{P}_T = \frac{k_{31}\alpha_1}{\alpha_2}$$

$$\hat{P}_L = \frac{\alpha_1^2 k_{21} k_{31}}{\alpha_2 \alpha_3}$$

Substitution of the estimated normalized prices into equations (5.3) – (5.5) yield the estimated values of $\hat{X}_B = (\hat{T}_B, \hat{L}_B, \hat{M}_B)$. The estimated allocative efficiency of the input set X_A is then given by $AE_A = \frac{P \cdot X_B}{P \cdot X_A}$.

EMPIRICAL RESULTS

Estimation of the production frontiers for both the participant and nonparticipant groups was accomplished by maximum likelihood.[8] The likelihood function was maximized using a slightly modified scoring algorithm (see Greene, 1980). The convergence criteria of $|\hat{\phi}_{i+1} - \hat{\phi}_i| \leq 10^{-4}$, where $\hat{\phi}_i$ denotes the parameter estimates for the i^{th} interation, was utilized. In addition to maximum likelihood, the frontiers were also estimated by a corrected ordinary least squares (COLS) estimator proposed by Greene (1980). The COLS parameter estimates are consistent and were used as starting values for the scoring algorithm.

The parameter estimates for both the COLS and maximum likelihood (ML) estimators are presented in Table 1. For both the participant and nonparticipant groups, each estimator yielded parameter estimates of the appropriate sign. Further, all parameter estimates with the exception of the output elasticity of land for the participant group are significantly greater than zero.

For the participant group, the output elasticity of labor was considerably larger than the corresponding elasticities of the other inputs. This appears reasonable given the labor intensive nature of farming in the Zona da Mata. Similar results were observed for the nonparticipant group. Both groups had very virtually identical output elasticities for intermediate materials.

A comparison of the parameter estimates for COLS and ML yields a similar pattern of parameter changes for both the participant and nonparticipant groups. In general, the ML estimator yielded a higher estimate for the output elasticity of labor and a lower estimate for the output elasticity of land as compared to the COLS estimator. The parameter estimates for intermediate materials showed little change.

These parameter changes are especially interesting given the implied relationship each frontier estimator has with the fitted average function. The COLS estimator yields a frontier that is a neutrally scaled version of the average function. While these estimates are consistent, they are not necessarily efficient. In contrast, the ML frontier estimator by virtue of the disturbance specification allows for the possibility that the frontier function may not be a neutrally scaled version of the fitted average function.

The relationship between the frontier function and the estimated average (OLS) function as well as the estimation efficiency gains obtained from ML estimation are to a large extent determined by the degree of skewness exhibited by the disturbance distribution. If the disturbance distribution is highly skewed, the "slope" parameters of the estimated frontier will differ considerably from the fitted average function and the efficiency gains from ML estimation will tend to be large. On the other hand, if the disturbance distribution is fairly symmetric the estimated frontier will bear close resemblence to the neutrally scaled average function and efficiency gains will be minimal.

For the $G(\lambda,P)$ distribution, as $P \to \infty$, the distribution becomes fairly symmetric, while as $P \to 2$, the distribution is highly skewed. Table 2 presents some summary measures for the estimated disturbance distribution. For the participant group. The estimated value of P was 16.33. The distribution is moderately skewed with the gain in asymptotic efficiency over the COLS estimator of roughly 14 percent. For the nonparticipant group, the estimated value of P was 35.27. The distribution appears to be relatively symmetric with the gain in asymptotic efficiency of ML over COLS being only 6 percent.

The estimated technical and allocative efficiencies for participant and nonparticipant groups by farm size are presented in Table 3.[9] The average technical efficiency for all participant farms was estimated to be approximately 19 percent while the estimated technical efficiency for nonparticipants was 6 percent. Thus, those farms which participated in the PRODEMATA program have estimated technical efficiencies that were on average at least three times as great as nonparticipant farms.

The estimated average allocative efficiency for all participant farms was 74 percent while for nonparticipant farms the average was 86 percent. The higher average allocative efficiency of the nonparticipant group may appear surprising at first. However, in light of Schultz' hypothesis which implies that traditional farmers are allocatively efficient, these results may be a manifestation of participant farmers adapting to implicit marginal decisions for new types of inputs. Thus, as participant farmers learn to allocate new resources these allocative efficiency measures may be somewhat lower than their nonparticipant counterparts.

One of the criticisms of previous credit programs has been that the farms which needed the least assistance received the most. Generally large farms receive more assistance than smaller farms. One of the primary goals of the PRODEMATA program was the explicit orientation of credit provisions and technical and extension assistance to smaller farms. The success of the PRODEMATA program in accomplishing this may be analyzed by viewing estimated efficiency measures by farm size.

For participant owned farms, the average technical efficiency estimates were very similar in all farm size categories. A comparison with the estimated technical efficiencies of the corresponding categories for nonparticipant farms reveals that increases in technical efficiency were relatively uniform across all farm sizes. It thus appears that not only was the PRODEMATA program been successful in increasing the technical efficiency of participant farms, but also, that these increases are fairly uniform for small farms as well as large.

Examination of estimated allocative efficiencies by farm size indicates that participant farms have marginally lower allocative efficiencies than nonparticipant farms for all farm owned size categories. Generally, the difference in allocative efficiency measures is about 10 percent. As mentioned previously, the lower allocative efficiency measures are probably a manifestation of participant farmers adapting to new production practices and inputs. It is interesting to note however that this occurance is fairly uniform in magnitude across various farm sizes.

The estimated average technical efficiency of sharecroppers was substantially higher than other owned farm categories in the participant group and marginally higher in the non-participant group. This may be attributable to the rather small numbers of participant sharecroppers. However, an alternative explanation is plausible. For the most part sharecroppers are part-time farmers. Thus in contrast to owned farms where labor is abundant, labor for sharecroppers is somewhat scarce. There may therefore be a tendency to utilize labor as well as other inputs more efficiently due to time constraints. Complementing this is the fact that sharecroppers tend to face explicit market prices for inputs whereas landowners face somewhat more implicit market prices for some inputs (notably land and labor). The incentives to be technically and allocatively efficient may therefore be somewhat greater for sharecroppers.

Summary and Conclusions

The use of agricultural credit programs as a policy tool for improving agricultural productivity and incomes of traditional farmers has a long history. The effectiveness of such programs have been extensively debated with no clear consensus emerging. In 1976, the PRODEMATA program was instituted in the Zona da Mata region of Brazil with the broad objective of inducing agricultural development.

The PRODEMATA program is somewhat unique in that credit provisions were tied closely with technical services and extension activities. Not only were the financial resources necessary to purchase modernized farm inputs supplied, but also the technical expertise to utilize them properly and efficiently was provided as well.

Estimates of technical efficiency for farms which participated in the PRODEMATA program compared to those of nonparticipating farms indicate that the program was successful as measured by technical efficiency gains. Generally, participant farms were three to four times more technically efficient than nonparticipant farms. Furthermore, the gains in technical efficiency were fairly uniform for various farm sizes. The PRODEMATA program appears to have been successful in providing benefits to small as well as large farms.

In general, participant farmers had estimated allocative efficiencies marginally lower than nonparticipant farmers. For both groups however, the relatively high allocative efficiencies appear consistent with Shultz' hypothesis that traditional farmers are allocatively efficient.

The lower allocative efficiency estimates of participant farms is likely to be a manifestation of learning to make marginal decisions with respect to new input sets. As familiarity with new production practices and inputs increases, allocative efficiency measures for participant farms should increase.

A potential limitation to the results of this analysis is the possibility that PRODEMATA was not really effective in improving technical efficiency. Rather, the results obtained were a manifestation of the fact that better farmers tended to participate in PRODEMATA. On the assumption that "better" farmers can be identified on the basis of socio-economic factors, a discriminant analysis was conducted to evaluate this chicken and egg dilemma.[10] The analysis indicated that indeed the PRODEMATA was effective in increasing technical efficiency.

The results of this paper indicate that PRODEMATA program was generally successful in increasing the technical efficiency of traditional farmers in the Zona da Mata region of Brazil. The extent to which these increases were the result of credit provisions alone, or technical and extension services alone is difficult to gauge. It seems clear, however, that when these two functions are effectively combined, beneficial results can be obtained.

Footnotes

[1]Other less frequently used measures of technical efficiency have been developed by Timmer (1971) and Fåre and Lovell (1978).

[2]In addition to the stochastic requirements above, generalized Farrell measures also require that the production function be strictly monotone increasing, continuous and quasi-concave.

[3]For many common production function specifications, the reduced forms of the implied cost function are known.

[4]Direct estimation of a frontier cost function for a fairly general production technology was not possible due to inadequate price data. Price data for the input measures were often not recorded in sufficient detail or lacked sufficient variation within the sample.

[5]A complete discussion of the data used in estimation is presented in Gomez (1983).

[6]As shown by Schmidt (1976) many of the programming methods used to obtain full frontier production functions are equivalent to maximum likelihood estimators. However, because the range of the disturbance distribution is not independent of the parameters being estimated, the regularity condition necessary to obtain statistically valid asymptotic standard errors is violated.

[7]Note that given the price vector P and output Y_o, $C(Y_o, P) \equiv K P_T^{\alpha_1} P_L^{\alpha_2} P_M^{\alpha_3} Y_0^r$ corresponds to the minimum cost of producing Y_o.

[8]In order to validate direct single equation estimation of the production frontiers, the behavioral assumption of expected profit maximization is maintained.

[9]Efficiency estimates were calculated from cost functions constructed from the ML parameter estimates in Table 1. The input prices used for land, labor and capital were CR$2780, CR$429.30 and CR$227.02 respectively. (see Gomez, 1984 for a more detailed discussion). All firms were assumed to face identical input prices. Given the small size of the Zona da Mata, this assumption appears reasonable.

[10]A detailed discussion of the discriminant analysis may be found in Gomez (1983).

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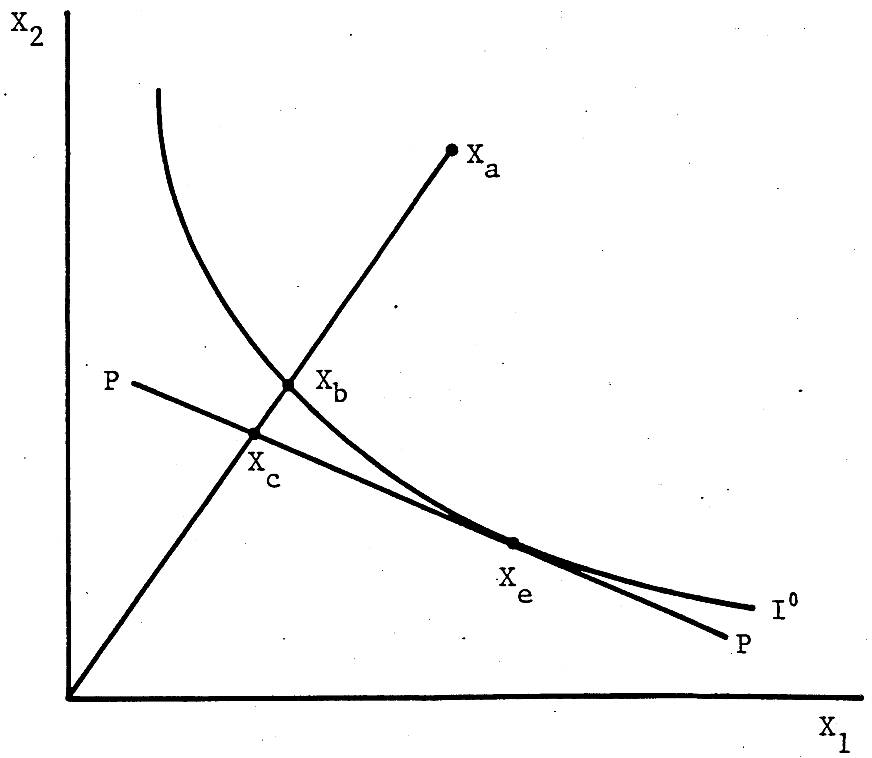

Figure 1. Farrell Efficiency Measures

Table 1. Estimated frontier production function parameters for COLS and maximum likelihood estimators

Estimator	Variables			
	Intercept	Land	Labor	Materials
COLS				
Participant	3.0897 (0.3433)[a]	0.0855 (0.0512)	0.7099 (0.0945)	0.2439 (0.0525)
Nonparticipant	4.7873 (0.2221)	0.1227 (0.0381)	0.5832 (0.0617)	0.2822 (0.0357)
Maximum likelihood				
Participant	3.3496) (b)	0.0481 (0.0448)	0.7948 (0.0587)	0.2535 (0.0512)
Nonparticipant	4.9950 (b)	0.09571 (0.0301)	0.65965 (0.0342)	0.2523 (0.0338)

[a]Asymptotic standard errors in parentheses.

[b]Less than 10^{-7}.

Table 2. Summary measures for the estimated disturbance distributions

Summary measure	Group: Participant	Group: Nonparticipant
$\hat{\lambda}$	8.3475 (0.8843)	11.6493 (1.0422)
$\hat{P}$	16.3315 (1.7146)	35.2710 (3.1376)
Asymptotic efficiency ratio[a]	1.1396	1.0601
Skewness[b]	0.4949	0.3368
Degree of excess[c]	0.3674	0.1701

[a]Computed by $\frac{\hat{P}}{\hat{P}-2}$

[b]Computed by $2\ \hat{P}^{-1/2}$

[c]Computed by $\frac{6}{\hat{P}}$

Table 3. Estimated average allocative and technical efficiency by farm size and participation in the Prodemata Program[a]

Efficieny Index	Sharecroppers	Farm Size (Hectare)				All farms
		0-10	10.01-50	50.01-100	>100	
Technical efficiency						
Participant	0.394 (.066)[a]	0.179 (.012)	0.175 (.007)	0.196 (.014)	0.202 (.021)	0.185 (.006)
Nonparticipant	0.071 (.005)	0.050 (.004)	0.060 (.009)	0.053 (.005)	0.056 (.007)	0.059 (.003)
Allocative efficiency						
Participant	0.901 (.047)	0.835 (.023)	0.750 (.012)	0.658 (.021)	0.609 (.022)	0.743 (.008)
Nonparticipant	0.880 (.020)	0.894 (.013)	0.850 (.011)	0.772 (.023)	0.703 (.0535)	0.857 (.016)

[a]Based on ML parameter estimates in Table 1.

[b]Asymptotic standard errors in parentheses.