Technical Efficiency, Managerial Ability and Farmer Education in Guatemalan Corn Production: A Latent Variable Analysis

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In this study it is argued that conflicting empirical results on the relationship between technical efficiency and education may be in part attributable to difficulties in the measurement of key variables. Calculation of technical efficiency with three alternative frontier methods for a sample of Guatemalan corn farms resulted in significant differences both in the average technical efficiency of the sample and the efficiency rankings of individual farms. Furthermore, following two-step procedures where technical efficiency is regressed against a set of explanatory variables, it is shown that the choice of efficiency measurement technique can alter the importance of education as a contributing factor to increased technical efficiency. An alternative approach is presented for investigating the relationship between education and efficiency while accounting for difficulties in the measurement of conceptual variables and measurement errors.

In economics, it is widely accepted that increased education for a firm's workers and managers has a positive influence on the firm's productivity level. Higher levels of education, presumably, allow workers to produce more from existing resources and enhance managers' abilities to effectively reallocate resources under changing economic conditions (Welch). The relationship between education and technical efficiency has been extensively investigated in agriculture (Fane, Huffman, Kumbhakar et al., Lockheed et al., Stefanou and Saxena, Bravo-Ureta and Pinheiro). Empirical evidence on the relationship between technical efficiency and education, however, has been rather mixed. While many studies provide empirical support for a strong positive relationship between education and technical efficiency, other studies find no association and, in few cases, a negative relationship is uncovered.[1]

In this study it is argued that difficulties associated with the measurement of education and technical efficiency are, at least in part, responsible for this mixed empirical evidence. It is further argued that when the relationship between technical efficiency and education is empirically analyzed, difficulties in the measurement of these key variables should be accounted for explicitly. For this purpose, a latent variable model is proposed to examine the relationship between technical efficiency and education. Within the proposed framework, technical efficiency is considered to be an imperfectly measured latent variable determined by another latent variable, the managerial ability of the farm operator. Multiple indicators obtained through alternative frontier methods are used to measure the latent technical efficiency. It is posited that the operator's managerial ability is determined by formal and informal education, exposure to extension services, experience, as well as personal talents and traits. Thus, within the proposed

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[1] Bravo-Ureta and Pinheiro, Lockheed et al., and Phillips reviewed a number of studies that provided empirical evidence on the relationship between technical efficiency and education. Bravo-Ureta and Pinheiro reviewed 30 frontier studies, 19 of which used education as an explanatory variable of technical efficiency. Sixty-four percent of these latter studies found a statistically significant positive relationship between technical efficiency and education. Lockheed et al. reviewed 18 such studies, 56 percent of which indicated a positive statistical relationship between technical efficiency and education. In the remaining 44 percent of these studies, the relationship was statistically not different from zero or was negative.

framework, education is one of several indicators that measure the latent managerial ability of a farm operator.

The proposed approach is empirically implemented for a sample of Guatemalan corn farmers. Choosing the sample from a developing country is appropriate for two reasons. First, improvements in technical efficiency and productivity growth are of particular importance to developing countries. High rates of population growth and poverty continue to apply significant pressures for increased production of food and fiber. Identification of structural factors that contribute to long-run improvements in efficiency and productivity growth is therefore of interest. Second, educational levels among farmers in developing countries are quite variable. Thus, the importance of education on managerial ability and technical efficiency can be more readily identified.

Education, Technical Efficiency and Difficulties in Measurement

Welch's argument that education enhances an individual's ability to collect and process information has, undoubtedly, a general appeal. In the context of developing countries, where the development process often entails technological innovations, greater education should allow a farmer to better utilize technical and market information on inputs and outputs. This improved ability to use information should result, in turn, in enhanced technical efficiency. Following this reasoning, most researchers consider education a homogeneous input stock that shifts the managerial ability of farm operators and, hence, their technical efficiency levels (Huffman, Kumbhakar et al., Stefanou and Saxena). Yet, others treat education as a homogeneous input flow that combines with conventional inputs according to some underlying substitution possibilities (Fane, Welch).

However, it may be altogether inappropriate to regard education as a *homogeneous* factor of production. Specifically, it is rather unlikely that education can be considered a homogeneous input stock that shifts farmers' managerial abilities in a uniform fashion. It is more likely that education has a variable influence on farmers' managerial abilities, and that this influence is contingent on a variety of personal characteristics such as intelligence, self-motivation, ability to learn from past experience, and managerial instinct. In other words, equal amounts of education are likely to affect the managerial ability of different individuals in distinct ways due to their diverse talents and personal characteristics.

Similarly, regarding education as a homogeneous input flow that combines with conventional inputs under some stable substitution possibilities is not reasonable. Personal attributes and characteristics of different individuals are likely to modify the manner in which education interacts with other factors of production. Thus, it is unsatisfactory to treat education as either a homogeneous input stock or flow in farm production.

Another issue that warrants closer attention is the empirical measurement of education. The number of years of schooling is the most often used measure of education. However, numerous factors determine the actual amount of education and knowledge acquired by an individual in a given number of years of schooling. Quality of education, type of curriculum, personal learning ability, self-motivation, and school attendance are some of these determining factors. Thus, measuring education simply by the number of years of schooling involves an unknown amount of measurement error.

Given the above considerations, we present an alternative view of the relationship between education and technical efficiency. Specifically, technical efficiency is assumed to be directly related to the managerial ability of a farmer.[2] This managerial ability is formed by relevant attributes of an individual's personality and talents, as well as by external influences. Formal and informal education and extension services are such external influences that may be important in shaping a farmer's managerial ability. The psychological process by which personal attributes, talents, and external influences interact to form managerial ability, however, is not well known. Furthermore, many of the personal characteristics and talents contributing to an individual's managerial ability are not directly measurable. Thus, managerial ability is regarded in this study as a latent variable. Education, farming experience, and relevant personal attributes and talents are considered, in turn, to be imperfect indicators of an individual's latent managerial ability. This treatment explicitly allows for errors in the measurement of education and its relationship to technical efficiency.

Technical efficiency itself, however, may pose

[2] The contribution of managerial ability to production and technical efficiency has been treated in previous studies in various ways. Mundlak and Hoch used covariance analysis to account for "management bias." Thus within their framework, technical efficiency is identical to managerial ability. In other studies, proxies of management (e.g. Weersink et al.) or management indices (e.g. Antle and Goodger) are used to account for differences in the efficiency of firms.

additional problems in measurement. The notion of technical efficiency is uniformly understood to be a measure of the deviation of a firm's output from the production frontier due to inability rather than misfortune. If the theoretical frontier was available and if the source of deviations from the frontier was known, technical efficiency could be measured in a straight forward manner. However, the production frontier has to be empirically estimated and arbitrary assumptions about the deviations from the frontier must be made. Numerous methods have been developed to accomplish these ends. These methods involve the use of alternative parametric and nonparametric estimation procedures and a variety of distributional assumptions about technical inefficiency and other random effects on a firm's output. The choice of methods for estimating the production frontier and measuring technical efficiency, however, appears to be consequential. In several recent studies, technical efficiency series calculated by alternative methods were found to differ markedly, even though they were based on the same body of data (Banker et al., Ferrier and Lovell, Kalaitzandonakes et al.). In cases where estimated efficiency series are not robust to the choice of estimation technique, structural relationships such as those between managerial ability and technical efficiency could be clouded simply by this choice. Yet, the choice of estimation approach in efficiency measurement is largely arbitrary and each procedure for measuring technical efficiency has distinct advantages and disadvantages.

This study deals with difficulties in the measurement of technical efficiency by treating the technical efficiency of any set of farms as a latent variable. Furthermore, farm-level technical efficiency series estimated with alternative methodologies are considered to be imperfect indicators of the latent technical efficiency. Based on the above considerations, the relationship between education, managerial ability, and technical efficiency can be analyzed within the framework of the following general model:

$$\text{(1a)} \qquad EFF^* = F(MANG^*;A) + v$$

$$\text{(1b)} \qquad Y = G(EFF^*) + e$$

$$\text{(1c)} \qquad X = H(MANG^*) + u$$

Equation (1a) suggests that the latent technical efficiency EFF^* of different farm operators is a function of their also latent managerial ability $MANG^*$ and a vector of other influences, A. Equation (1b) indicates that a vector of indicators Y of technical efficiency can be used to imperfectly measure the latent technical efficiency of each farm operator subject to error e. Similarly, equation (1c) suggests that a vector of relevant variables, X, can be employed as indicators to measure the latent managerial ability of a farmer operator subject to measurement error u.

As specified above, model (1) can be cast within the general framework of structural equations with latent variables (Bollen). The proposed approach is empirically implemented in this study for a sample of Guatemalan corn farmers. First, three indicators of technical efficiency for the farms in the sample are obtained through alternative frontier measurement procedures. Subsequently, personal data of the farm operators are utilized to assess the hypothesized relationships between technical efficiency, managerial ability, and education. Traditional regression results assessing the importance of education on technical efficiency are also presented in order to provide a reference for the proposed latent variable approach.

Technical Efficiency: Definitions and Measurement

In this section we advance the argument that technical efficiency is a latent variable by extending the discussion on the difficulties associated with its empirical measurement. Along the way, some basic notation is provided and carried into the discussion of the empirical models that are estimated in the following section.

Let a production technology, where inputs $x = (x_1, \ldots, x_n) \in R^n{}_+$ combine to produce a single output $y \in R_+$, be represented by an input correspondence $y \rightarrow L(y) \subseteq R^n{}_+$. The input requirement set $L(y)$ denotes all the input vectors that are capable of producing at least the output level y. A well behaved technology satisfies the following properties (Shephard):

$$\text{(2a)} \qquad 0 \notin L(y),\ y > 0 \quad \text{and} \quad L(0) = R^n_+;$$

$$\text{(2b)} \qquad x \in L(y) \Rightarrow \lambda x \in L(y), \quad \lambda \geq 1;$$

$$\text{(2c)} \qquad L \text{ is a closed correspondence;}$$

$$\text{(2d)} \qquad L(\phi y) \subseteq L(y), \quad \phi \geq 1.$$

Property (2a) suggests that a positive output cannot be attained with zero inputs and that all productive factors can be allowed to remain idle. Property (2b) implies weak disposability. Hence, although wasteful use of factors is allowed, such use does not cause the reduction of output. Property (2c) affirms that efficient points exist. The closed nature of the input requirement set assures that L includes its boundaries and thus efficient production is possible. Finally, property (2d) implies weak monotonicity and allows for variable returns to scale. For example, in the case of constant returns to scale L.4 implies that $L(\phi y) = \phi L(y)$. For decreasing returns to scale, the monotonicity assumption indicates that $L(\phi y) \subset \phi L(y)$.

In measuring technical efficiency, two subsets of $L(y)$ are of interest, the isoquant $IL(y)$ and the efficient subset $EL(y)$. These subsets are defined as follows

$$IL(y) \equiv \{x{:}x \in L(y),\ \lambda x \notin L(y),\ \lambda \in [0,1]\} \quad y > 0 \tag{3a}$$

$$EL(y) \equiv \{x{:}x \in L(y),\ z \leq x \Rightarrow z \notin L(y)\} \quad y > 0. \tag{3b}$$

From these definitions it is apparent that the isoquant $IL(y)$ defines the outer boundary or frontier of the input requirement set $L(y)$ and $EL(y) \subseteq IL(y)$. Theoretically, an input vector x is technically efficient in the production of output y if and only if $x \in EL(y)$. $EL(y)$ is assumed to be bounded and non-empty for $y \in [0,\infty)$. Hence, for every positive output there exists a finite input vector representing efficient production. Any deviation of the input vector x from the efficient subset $EL(y)$ due to wasteful use of resources is considered to be technical inefficiency.

An input vector that satisfies (3b) for a given output level y is fully efficient. However, while this definition is straight forward, in order to use it in practice it is necessary that the reference technology and its efficient subset be empirically defined. Unfortunately, many unresolved difficulties remain in matching the empirical efficient subset with its theoretical counterpart. Several measures exist that operationalize the theoretical concept of technical efficiency. The best known is the Farrell measure which is given by

$$F(x,y) = \min \{\lambda{:}\lambda x \in L(y),\ \lambda \geq 0\} \tag{4}$$

Technical efficiency within this framework is measured as the equiproportional (radial) reduction in all inputs that is possible while maintaining production at level y. A departure from the theoretical concept of technical efficiency is already apparent. $F(x,y)$ has as a reference set the isoquant $IL(y)$ rather than the efficient subset $EL(y)$. That is, while an equiproportional reduction in x will intersect $IL(y)$, there is no guarantee that such a process must intersect $EL(y)$.

Empirical application of (4) leads to further departures from the theoretical concept of technical efficiency. Measurement of $F(x,y)$ implies the need for empirical measurement of the frontier $IL(y)$. A variety of empirical techniques have been proposed regarding (a) the way the frontier is constructed (through statistical and programming techniques); (b) the way the frontier is specified (parametric or non parametric); (c) the way deviations from the frontier are interpreted (as purely technical inefficiency or as technical inefficiency and noise). As a result, numerous empirical measures of $F(x,y)$ have been developed. Unfortunately, none of these measures is free of shortcomings in approximating the Farrell measure and its theoretical analogue (Forsund et al., Lovell and Schmidt).

Divergence of empirical frontier measures of technical efficiency from their theoretical analogue are likely to be further accentuated by statistical noise, clerical errors, and other data inefficiencies and measurement errors. As a result, alternative empirical measures of technical efficiency are considered imperfect indicators of the theoretical (latent) technical efficiency. In this study, three Farrell-type indicators are used to measure the latent technical efficiency. Specifically, technical efficiency is empirically measured relative to a deterministic statistical frontier, a stochastic frontier, and a non-parametric frontier constructed by programming techniques (also referred to as data envelopment analysis or DEA). The choice of the measurement procedures in this study is guided primarily by the popularity of these procedures in empirical research.

Measuring Technical Efficiency for a Sample of Guatemalan Corn Farmers

We measure technical efficiency in corn production for a sample of 82 family farms in Guatemala (Dunn).[3] The farmers in the sample were all participants in market-based land reform programs. Under these land programs, low-income, landless families were provided mortgage financing to purchase small holdings of land. In many cases, production credits were also provided. Prior agricultural experience was a requirement for participation in the program.

Input-output data used for the measurement of technical efficiency included physical measurement of inputs and output in corn production. In particular, land was measured in hectares, labor was measured in work days, machinery and animal

[3] The survey by which the data were collected was administered in 1990. Input-output information is from the 1989–90 season.

traction were measured in hours of operation, and agrichemicals were measured by their monetary value. The typical corn enterprise in the sample was characterized by its heavy reliance on family labor and the cultivation of a small land area.

Most households in the sample also grew either coffee or vegetable crops in land parcels distinct from those used for corn production. The inputs used in this study were exclusive to corn production. An implicit assumption of the allocation of inputs among different outputs produced by the households was that their technology was non-joint in inputs.

Additional survey data used in the study included characteristics of the male head of household such as education, years of experience growing corn, and number of contacts with the program-sponsored agricultural technician. Means and standard deviations of output, inputs, and household characteristics of the sample used are presented in Table 1.

Measuring Technical Efficiency with a Deterministic Statistical Frontier. Assume that the corn production in Guatemala is of the Cobb-Douglas variety. Hence, the reference technology of the firms in the sample of interest can be written as

$$L(y) = \{x{:}y \leq A \prod_{i=1}^{n} x_i^{ai}\}. \tag{5}$$

The weak inequality in (5) can be converted into an equality by expressing actual output as

$$y = A \prod_{i=1}^{n} x_i^{ai} \exp\{u\}, \tag{6}$$

where $u \leq 0$ represents technical inefficiency relative to the deterministic frontier. The parameters of the production frontier and the density of u can be estimated with a variety of methods; the easiest of these methods is corrected ordinary least squares (COLS). If μ is the mean of u, then (6) can be rewritten in its logarithmic form as

$$\ln y^k = (\ln A + \mu) + \sum_{i=1}^{n} a_i \ln x_i^k + (u^k - \mu),$$
$$(7) \quad k = 1, \ldots, K$$

where K is the total number of firms in the sample. Within this specification, the new error term has an expected value of zero and (7) can be estimated with OLS to obtain best linear unbiased and consistent estimates for the a_i's and the new constant term $(\ln A + \mu)$. Several different procedures are available for obtaining a consistent estimate of A. One procedure proposed by Gabrielson involves neutrally shifting the frontier until it envelops the data. That is, the OLS parameter estimate for the constant is shifted upwards until no residual is positive. This procedure provides a consistent estimate for A for any one-sided distribution of u with positive density in the neighborhood of zero (Lovell and Schmidt). Within this framework, the technical efficiency of the k^{th} firm is measured as the deviation of y_k from its fitted value, as

$$EFF_1^k = \exp\{u^k\} = \exp\{\ln A + \sum_{i=1}^{n} a_i \ln x_i^k - \ln y^k\}$$
$$(8) \quad k = 1, \ldots, K.$$

Following the procedures described above, the parameters of the deterministic frontier were estimated and are reported in Table 2. Indices of technical efficiency for each firm in the sample of interest were also obtained and their frequency distribution is reported in Table 3. Technical efficiency indices generated using the COLS procedure are indicated as EFF_1. The level of technical efficiency of the firms in the sample varied from a minimum of 0.21 to a maximum of 1.00 while the average technical efficiency level for all firms was 0.52.

The frequency distribution of the firm-level technical efficiency indexes also indicates that the majority of the firms exhibited significant technical inefficiencies. Specifically, 73 out of the total of 82 farms (or 89 percent of all farms) were found to produce 70 percent or less of their potential due to technical inefficiency. However, the estimated

Table 1. Input-Output and Farm Operator Personal Data for 82 Guatemalan Corn Farms

Variable	Mean	Standard Dev.
Output (qq)[a]	103.40	93.18
Land (ha)	1.56	1.29
Chemicals (q)[b]	332.04	313.54
Animal traction (hrs)	14.49	23.40
Machine (hrs)	9.41	9.29
Operator Labor (days)	55.81	30.04
Other Labor (days)	79.11	69.61
Education (years)	1.93	1.89
Extension (contact days)	3.87	8.02
Experience (years)	5.47	2.33

[a]qq = quintales, a dry measure equal to 100 lbs.
[b]q = quetzales, a monetary unit equal to US$ 0.28 at the time of the data collection.

Table 2. Parameter Estimates of Production Frontiers. "t" Values in Parentheses

	Method for Generating Efficiency Series	
Parameter	COLS	ML
Intercept	2.71 (6.4)	2.92 (7.2)
Land	0.72 (6.6)	0.65 (6.9)
Chemicals	0.10 (1.9)	0.13 (2.7)
Animal Traction	0.08 (3.7)	0.08 (3.9)
Machine	0.22 (3.7)	0.19 (3.7)
Operator Labor	0.05 (0.7)	0.05 (0.7)
Other Labor	−0.02 (−0.7)	−0.03 (−0.9)
Altitude	0.23 (2.6)	0.26 (3.3)
σ^2_e		0.42 (5.1)
σ^2_v		0.14 (2.6)
Adj R-squared	0.933	
Mean Log Likelihood		−0.16

level of technical inefficiency for the firms in the sample is most likely overstated. This is because deterministic production frontiers designate any deviation from the frontier as technical inefficiency. Hence, deviations due to bad weather, machine breakdowns, or other factors outside the control of the firm, including statistical noise, are all lumped together with actual technical inefficiencies.

Measuring Technical Efficiency with a Stochastic Statistical Frontier. Unlike deterministic frontiers, stochastic frontiers attempt to differentiate technical inefficiency from statistical noise and random influences outside the control of the firm. Assuming that the technology is defined as in (5), actual output y is now specified as

$$y = A \prod_{i=1}^{n} x_i^{ai} \exp\{v + e\}. \tag{9}$$

Within this specification, deviations of actual input-output combinations from the frontier due to statistical noise, measurement error, and other random shocks are captured by v while technical inefficiencies are captured by $e \leq 0$ (Aigner et al., Meeusen and Van den Broeck).

Assuming that the two-sided error term is normally distributed ($v \sim N(0,\sigma_v^2)$) and that the one-sided inefficiency term is distributed half normal ($e \sim |N(0,\sigma_e^2|$), the parameters of the frontier and the density functions of v and e can be estimated by maximizing the log-likelihood function

$$\ln\mathcal{L} = K \ln(2/\pi)^{1/2} + K \ln\sigma^{-1} + \sum_{k=1}^{K} \ln[1 - F(u_k\lambda\sigma^{-1})] - \tfrac{1}{2}\sigma^2 \sum_{k=1}^{K} u_k^2; \tag{10}$$

where u is the sum of v and e, σ is equal to $(\sigma_v^2 + \sigma_e^2)^{1/2}$, λ is the ratio of σ_e over σ_v, and F is the standard normal distribution function. Firm-level estimates of technical efficiency can be derived by estimating the mean of the conditional distribution of e given u (Jondrow et al.). Hence technical efficiency for the kth firm is given by

$$EFF_2^k = E(e_k \mid u_k) = \sigma* \cdot \left[\frac{f(u_k\lambda\sigma^{-1})}{1 - F(u_k\lambda\sigma^{-1})} - u_k\lambda\sigma^{-1}\right] \quad k = 1, \ldots, K; \tag{11}$$

where $\sigma* = (\sigma_v^2\, \sigma_e^2/\sigma^2)^{1/2}$.

Following the above procedures, maximum likelihood (ML) estimates of the parameters of the stochastic production frontier as well as the density functions of v and e were derived for the firms in the sample of interest and are reported in Table 2. A frequency distribution of the farm-level technical efficiency indices is provided in Table 3. The technical efficiency indices generated using the stochastic frontier are indicated as *EFF*2. Technical efficiency of the firms in the sample was found to vary from a minimum of 0.37 to a maximum of 0.93 with the average being equal to 0.74. Using this second technique, the firms in the sample were determined to be substantially more technically efficient than indicated by the deterministic frontier. In particular, 50 out of a total of 82 firms (or 61

Table 3. Frequencies of Technical Efficiencies for 82 Guatemalan Farms

Frontier Estimation Method	Technical Efficiency Index							Average Technical Efficiency
	<0.4	0.4–0.5	0.5–0.6	0.6–0.7	0.7–0.8	0.8–0.9	>0.9	
COLS (EFF_1)	17	20	19	17	5	3	1	0.52
ML (EFF_2)	1	5	10	16	15	28	7	0.74
DEA (EFF_3)	0	0	3	3	9	6	61	0.93

percent of all farms) were found to produce 70 percent or better of their potential. It appears that a large portion of the technical inefficiency attributed to the firms using the deterministic frontier are dismissed as statistical noise within the framework of the stochastic frontier.

Unfortunately, the stochastic frontier approach is not without shortcomings of its own. *A priori* assumptions about the functional form of the frontier and the distributional properties of inefficiency e and statistical noise v are required. These assumptions are largely arbitrary and it is not clear how robust the results are to such assumptions (Lovell and Schmidt). Furthermore, the firm-level index of technical efficiency given by (11) is not consistent (Jondrow et al.).

Measuring Technical Efficiency with a Nonparametric Frontier. Nonparametric frontiers overcome some of the limitations of the statistical frontier approaches employed above. Specifically, no restrictive assumptions need to be made about the functional form of the frontier or the distribution of inefficiency. Instead of attempting to fit a regression surface through the center of the data, nonparametric frontier procedures lay a piecewise linear surface on the top of the observations. Within this framework, a convex hull is constructed based on observed input-output combinations using programming techniques.

The input requirement set $L(y)$ for a sample of K firms can then be constructed as

$$(12)\quad L(y) = \{x\colon Yz \geq y,\ Xz \leq x,\ z \in R^n_+\}$$

where $Y \equiv [y^1, \ldots, y^K]$ is a k-vector of outputs, $X \equiv [x^1, \ldots, x^K]$ is an nxK matrix of inputs, z is a K-vector of intensities, and y^k and x^k are the output and input levels of the k^{th} firm. Technical efficiency for the k^{th} firm is measured by

$$(13)\qquad EFF^k_3 = \min\{\lambda\colon \lambda x^k \in L(y^k)\}.$$

Hence, technical efficiency within this framework is measured as the radial reduction of the inputs utilized by the k^{th} firm that would still result in an output level y^k.

The linear program employed to empirically calculate the level of technical efficiency for the k^{th} firm within the framework of DEA can be specified as

$$(14a)\qquad \min \lambda$$

$$(14b)\qquad \text{s.t.}\quad Yz \geq y^k$$

$$(14c)\qquad \lambda x^k - Xz \geq 0$$

$$(14d)\qquad z \geq 0,\ \lambda = \text{free}.$$

Problem (14) was solved 82 times, once for each firm, to obtain the efficiency score for each individual firm in the sample. The frequency distribution of the technical efficiency indices for the firms in the sample estimated by DEA are presented in Table 3. The level of technical efficiency varied from a minimum of 0.49 to a maximum of 1.00 with the average level of technical efficiency approximately 0.93. Thus, while the first two frontier procedures uncovered substantial inefficiencies—a result consistent with previous developing country studies (e.g. Bravo-Ureta and Pinheiro)—the DEA frontier approach suggests that technical inefficiencies in the sample are minimal.

It should be noted that in the original formulation of problem (14), an additional constraint which required the k intensities add up to one was included. Such a constraint allows for non-constant returns to scale. However, since in both statistical frontiers returns to scale were found to be approximately constant, problem (14) was re-estimated without the constraint. Thus, constant returns to scale were imposed *a priori* in the estimation of the DEA frontier. The efficiency series for the firms in the sample obtained with and without the unit constraint had a correlation coefficient of 0.97. Thus, it appears that the imposition of constant returns to scale on the production technology of the sample studied was inconsequential.

Simple inspection of the results reported in Table 3 indicates significant differences in both the frequency distributions and the average rates of technical efficiency under the three alternative measurement procedures. Furthermore, the Spearman correlation coefficients between the COLS efficiency series and the ML and DEA series were 0.93, and 0.48 respectively, while the correlation coefficient between the ML and DEA series was 0.47. Thus, significant differences in the efficiency rankings of the firms are also observed from one estimation procedure to another. Given that there is a unique value for each farm's true level of technical efficiency during the crop year represented in the sample, the observed instability of the estimated efficiency indices and rankings tends to support the argument that empirical measures of technical efficiency are imperfect indicators of their latent theoretical analogue.

Technical Efficiency and Education: Empirical Evidence

It has already been shown that the choice of measurement technique substantively affects the estimated relative efficiency of the farms in the sam-

Table 4. Maximum Likelihood Parameter Estimates of Logit Models. "t" Values in Parentheses

	Method for Generating Efficiency Series		
Parameter	COLS	ML	DEA
Intercept	−2.26	−1.57	1.248
	(−1.50)	(−1.19)	(1.01)
Education	0.286	0.310	−0.096
	(2.08)	(2.40)	(−0.84)
Experience	−0.012	−0.079	−0.111
	(−0.04)	(−0.35)	(−0.53)
Technician Contact	0.056	0.099	−0.012
	(1.83)	(2.10)	(−0.46)
Mean Log Likelihood	−36.4	−41.7	−54.7

ple. The next step is to evaluate whether the choice of technique could influence the assessment of the relationship between efficiency and education.

The most common approach to evaluating the impact of variables hypothesized to influence technical efficiency is regression analysis. Within this framework, technical efficiency for a sample of firms is first obtained through a frontier procedure and this efficiency series is subsequently regressed against a set of explanatory variables.[4] OLS procedures are most often used in the regression analysis. Weersink et al., however, pointed out that since the dependent variable is bounded at one, the standard OLS assumptions are violated. They proposed that a logit or censored model should be used instead. In this study, a logit model is used to evaluate the influence of education, extension, and farming experience on the estimated technical efficiency series.

Table 4 reports the results from three maximum likelihood estimations of the logit model. The three estimations differ only in the data used for technical efficiency, the dependent variable. These data came from the three efficiency series generated using the COLS, ML, and DEA techniques. Estimations based on the COLS and ML efficiency series indicate a positive relationship between education and technical efficiency that is statistically significant at conventional levels. By contrast, the results based on the DEA efficiency series do not indicate a statistically significant relationship between education and technical efficiency. Hence, there is evidence to suggest that the relationship between technical efficiency and education evaluated within the traditional two-step approach can be clouded simply by the selection of a method for estimating the frontier function.

In light of the results derived so far and based on arguments presented earlier, an alternative approach for empirically assessing the structural relationship between technical efficiency and education is now presented. Following the conceptual model in (1), true technical efficiency of the Guatemalan corn farms is regarded as latent. The technical efficiency series derived above are considered only imperfect indicators of the latent technical efficiency. In turn, technical efficiency is hypothesized to relate directly to a farmer's managerial ability. The managerial ability of each individual farmer in the sample is also considered to be latent in accordance with the earlier hypothesis. Formal education, farming experience, and contact with the extension specialist are all assumed to contribute to the managerial ability of Guatemalan farmers. Education is measured, as in previous studies, by years of schooling. However, in this study the measurement error related to education is explicitly accounted for within the specification introduced below. Farming experience is measured by years of experience in corn production and extension exposure is measured by days of contact with the extension specialist during the year which includes the growing period.

Based on these assumptions, a relevant empirical model can be specified as follows:

$$EFF^* = \gamma\, MANG + z \tag{15}$$

$$EFF_1 = \lambda_1\, EFF^* + \epsilon_1 \tag{16a}$$

$$EFF_2 = \lambda_2\, EFF^* + \epsilon_2 \tag{16b}$$

$$EFF_3 = \lambda_3\, EFF^* + \epsilon_3 \tag{16c}$$

$$EDUC = \mu_1\, MANG + \delta_1 \tag{17a}$$

$$EXTN = \mu_2\, MANG + \delta_2 \tag{17b}$$

$$EXPR = \mu_3\, MANG + \delta_3 \tag{17c}$$

Equation (15) specifies the structure of the unobserved true technical efficiency EFF^* which is considered a function of managerial ability $MANG$. Measurement equations (16a) through (16c) indicate that the three calculated efficiency series are considered indicators of the unobserved

[4] The two-step procedure has been criticized by several authors in the past. Kumbhakar et al. have argued that the estimated technical coefficients and technical efficiency indices are biased when the determinants of technical efficiency are not included in the first step of the regression. They provided a one-step procedure which determines the influence of socioeconomic variables on technical efficiency while estimating the technical coefficients of the production frontier. Kalirajan, on the other hand, has defended the practice of the two-step regression on the basis that socioeconomic variables have a roundabout effect on production.

true technical efficiency. Errors in the measurement of technical efficiency are denoted by ϵ_1, ϵ_2, and ϵ_3. Measurement equations (17a) through (17c) suggest that education (*EDUC*), farming experience (*EXPR*), and extension contact (*EXTN*) are indicators of the unobserved managerial ability of the farmers. Errors in the measurement of managerial ability are denoted by δ_1, δ_2, and δ_3.

The most common estimation procedure for empirical latent variable models is that of maximum likelihood where the following loss function is minimized (Bollen, p. 107):

$$(18)\quad \ln L = \ln|\Sigma(b)| + tr(S\,\Sigma^{-1}(b)) - \ln|S| - \text{constant}.$$

In specification (18), S is the sample covariance matrix of the observed variables while $\Sigma(b)$ is the covariance matrix of the observed variables when they are expressed as functions of the parameter vector b. In essence, estimation of the parameter vector involves the choice of b so that $\Sigma(b)$ is as close to S as possible.

The fitting function in (18) derives from the assumption that the observed variables follow a multinormal distribution. In many cases such an assumption is violated. Browne has shown that even when the multinormality distributional assumption is violated, maximization of (18) still leads to consistent parameter estimates. However, the variances of the parameter estimates must be adjusted to reflect departures from multinormality. Appropriate procedures for such adjustments have been provided by White. When departures from multinormality exist, estimates from (18) should be referred to as "pseudo maximum likelihood" estimates (Arminger and Schoenberg).

Most of the observed variables in this study failed univariate normality tests. For this reason, the parameters of the empirical model (15)–(17) were estimated through pseudo maximum likelihood procedures and their standard errors were estimated following White's procedures. All the variables in equations (15) through (17) were defined as deviations from their means and hence no constants were specified. The values for the factor loadings λ_1 and μ_2 were set equal to one. Such a normalization was necessary in order to define the measurement units (scale) for latent variables which were measured by multiple indicators. The estimated parameters of equations (15) through (17) are reported in Table 5. The estimated value of γ is positive and statistically significant at the 0.05 level indicating that a positive relationship between the latent technical efficiency *EFF** and managerial ability *MANG* exists. The factor loadings λ_2 and λ_3 are both positive and statistically significant suggesting that both the ML and the DEA efficiency series are positively related to the unobserved true efficiency series. Similarly, the factor loading μ_1 is positive and statistically significant indicating that more formal schooling is positively correlated with more managerial ability for the farmers in the sample. Farming experience is not found to be strongly related with managerial ability.

Table 5. Standardized Parameter Estimates of the Latent Variable Model[a]

Parameter	Estimated Value	t-value
γ	1.703	4.05
λ_1	0.950[b]	—
λ_2	0.979	13.76
λ_3	0.497	3.77
μ_1	0.069	1.97
μ_2	0.142[b]	—
μ_3	−0.009	−0.11
varϵ_1	0.096	1.59
varϵ_2	0.042	0.56
varϵ_3	0.752	6.07
varδ_1	0.979	2.70
varδ_2	0.995	6.52
varδ_3	0.999	3.87
varz	−1.901	−1.52
Coefficient of Determination for EFF$_1$, EFF$_2$, EFF$_3$		0.97
χ^2 Statistic (8 d.f.)		6.75
Probability > χ^2		0.56
GFI		0.97
AGFI		0.92

[a]Standardized coefficients are defined as the mean response, in standard deviation units, of the dependent variable for one standard deviation change in an explanatory variable.
[b]Parameters constrained through normalization.

Several measures of goodness of fit for the estimated model are also provided in Table 5. The coefficient of determination for EFF_1, EFF_2, and EFF_3 indicates how well these variables jointly describe, as measurement instruments, the latent dependent variable EFF^*.[5] This coefficient was estimated to be 0.972, thus indicating that EFF_1, EFF_2, and EFF_3 jointly measure EFF^* quite effectively. Three measures of overall model fit are also provided in Table 5. The χ^2 test statistic provides a means for testing the hypothesis H_0: $\Sigma(b) = \Sigma$. Thus, the χ^2 statistic is a simultaneous test

[5] The coefficient of determination for the three efficiency indicators is equal to $1 - (|\theta_\epsilon|/var_{eff^*})$, where $|\theta_\epsilon|$ is the determinant of the estimated covariance matrix of the measurement errors in equations (16a) through (16c) and var_{eff^*} is the estimated variance of EFF^*.

for all residuals $\Sigma - \Sigma(b)$ are zero and provides an overall measure of model fit. The probability level accompanying the test statistic is the probability of obtaining a χ^2 value larger than the value obtained if H_0 is correct. Thus, low values of χ^2 indicate a good model fit and vice versa. Following Tanaka and Huba, two additional measures of overall model fit are calculated. The first, the Goodness of Fit Index (GFI), measures the relative amount of variances and covariances in the sample covariance matrix predicted by the estimated covariance matrix $\Sigma(b)$. The Adjusted GFI (AGFI) adjusts for degrees of freedom relative to the number of variables. Both such measures have an upper limit of 1 indicating perfect overall model fit. All three measures of overall model fit indicate a satisfactory fit for the specified model. Thus, the measures of fit along with the statistical significance of the estimated coefficients indicate that the data in the sample tend to support the conceptual model and its implied parameter restrictions.

One problem with the results is that the estimated variance of z is negative and hence inadmissible. Although the parameter estimate is statistically not different from zero, there is little consolation from this result since a zero error variance would be equally inadmissible as it would imply that *MANG* is a perfect measure of *EFF**. Similarly, the variances of measurement errors ϵ_1 and ϵ_2, being statistically not different from zero, are also questionable.[6] Simulation work by Boomsma and by Anderson and Gerbing determined that small sample sizes frequently lead to negative or zero error variances, irrespective of the appropriateness of the conceptual model. Anderson and Gerbing suggested sample sizes of 150 observations or more to reduce the chances of inadmissible values. Given that our sample of 82 firms could not be increased, such remedy was not possible. An attempt to impose a non-negativity constraint on var_z resulted in a near zero and non-significant parameter estimate. Thus, the inadmissibility of the parameter var_z cannot be remedied within the specified model. It should be noted, however, that the estimated values of the remaining parameters are not particularly sensitive to the value of var_z. Imposition of the non-negativity constraint left the parameter estimates almost unchanged.

[6] Zero error variances for ϵ_1 and ϵ_2 imply that EFF_1 and EFF_2 are near perfect indicators of *EFF**. Such result would seem to endorse the use of COLS and ML as appropriate indicators of the unobserved *EFF**. However, given the small sample size in our study and the inadmissibility of var_z, it is more likely that we are experiencing some of the problems identified in Boomsma and in Anderson and Gerbing. Inferences about the suitability of different efficiency measurement techniques as appropriate indicators of *EFF** should be deferred to studies with larger sample sizes.

Summary and Conclusions

In this study it was argued that conflicting results on the relationship between technical efficiency and education may be in part attributable to difficulties in the measurement of technical efficiency and education. Calculation of technical efficiency with three alternative frontier methods for a sample of Guatemalan corn farms resulted in significant differences both in the average technical efficiency of the sample and the efficiency rankings of individual farms. Furthermore, following two-step procedures where technical efficiency is regressed against a set of explanatory variables, it was shown that the choice of efficiency measurement technique can alter the importance of education as a contributing factor to increased technical efficiency.

An alternative approach was presented for investigating the relationship between education and efficiency while accounting for difficulties in the measurement of conceptual variables and measurement errors. Within the proposed approach, education was viewed as an external influence that contributes to an individual's managerial ability which, in turn, has a direct effect on technical efficiency. Both managerial ability and technical efficiency were considered latent variables. Thus, the empirical implementation of the proposed framework relied on a latent variable model.

Empirical results from the estimated latent variable model indicated that more education was positively correlated with greater managerial ability on the part of the farm operator. Furthermore, managerial ability was found to have a positive influence on technical efficiency. Thus, the empirical results of the present study tend to support the hypothesized conceptual model.

In a more general context, the results of this study suggest that inferences based on efficiency studies should be cautious. Thomas and Tauer questioned the relevance of absolute efficiency measures and suggested that efficiency should be used primarily as a relative performance measure. The results in this study indicate that technical efficiency, even when used as a relative performance measure, may not be particularly dependable when difficulties in the empirical measurement of conceptual variables and other measurement errors are not explicitly accounted for. This study provides a viable alternative for empirically analyzing the sources of improved efficiencies while explicitly incorporating conceptual variables and measurement errors in the estimation.

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