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TECHNICAL, COST AND PROFIT EFFICIENCY: A MICRO-LEVEL STUDY

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I. Introduction

Production efficiency is usually assumed in microeconomic theory. In particular, a single production function is supposed to exist for all producers in the industry. Output may be random due to variation in the levels of uncontrollable inputs (e.g. weather in agricultural production; power failures in industry); however *expected value* of output is identical for decision-makers using the same input bundle. Further, in general it is assumed that producers equate marginal rates of transformation (either factor-factor, factor-product or product-product) to relevant price ratios. That is, costs are minimized and profits are maximized given the technology available at a point in time. Assuming absence of waste is convenient for understanding the workings of the price system; however, it appears to be overly restrictive for micro (and particularly management) oriented inquiries.

The efficiency assumption has been increasingly challenged. Starting in the mid 1960's various approaches have been developed for introducing inefficiency in models of firms. Harvey Leibenstein's *X-efficiency* theory (Leibenstein, 1966), as well as Herbert Simon's *satisficing* approach to human behavior (Simon, 1978) underpinned many of the efforts that were to follow. Recent literature reviews (e.g. Ley, 1990) suggest a substantial interest in production efficiency issues.

The efficiency debate has implications for policy. If firms and organizations are efficient, output can only be increased by augmenting the use of inputs. In the presence of slack, however, additional output can be forthcoming by appropriate reorganization of resources. The above considerations are relevant both for firms, as well as for decision units with objective functions other than profit maximization. Efficiency research is particularly important in countries undergoing structural transformation (e.g. Argentina) where shifts in production possibilities as well as in price ratios call for changes in the way things are done. As an example, consider the results of a study by the Mc Kinsey Global Institute (1994). In the early 1990's labor productivity in key economic sectors of Argentina was between one-third and two-thirds of that of the U.S.[1] Lower labor productivity can be the result of differences in factor prices (and hence in optimum labor/capital ratios); however it can also be caused by management practices and the competitive environment in which the firms operate. If the latter is the case, output increases can be forthcoming by improving managerial effectiveness, and not only by increasing the quantities of (conventional) inputs.

This paper analyzes efficiency of a panel of firms (combined time-series and cross-sectional observations). In particular, the question to be answered is whether efficiency values derived from empirical studies allow inferences on "management effectiveness" to be made. Attention is focused on technical, cost and profit efficiency dimensions. The firms comprising the sample belong to the Argentine agricultural sector.

II. Theory: Technical, Cost and Profit Efficiency

Technical Efficiency: Let X_{it} represent the *1xj* vector of inputs used by firm *i* in period *t*. Output forthcoming is $Y_{it} = f(X_{it})$. The function $f(.)$ maps inputs into the *maximum* output attainable. In real-world production processes, *how* inputs are used is as important as *how much* of these are used. In their simplest form, efficiency studies postulate the production function as:

[1] $Y_{it} = \alpha_{it} f(X_{it})$

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[1] Figures are 37 percent for steel, 52 percent for processed foods, and 66 percent for telecommunications.

where $\alpha_{it} \in [0, 1]$ represents a production-function shifter that indicates the extent to which inputs X_{it} are transformed into output Y_{it}. Management can be posited to be the main factor affecting α_{it}, thus:

$$[2] \quad \alpha_{it} = g(M_i)$$

The objective of efficiency measurement is to gauge to what extent differences in output are attributable to differences in *M*. In particular, for a set of producers $i = 1, \ldots, I$, *Technical Efficiency* can be defined as the ratio between actual and potential output:

$$[3] \quad TE_{it} = y^{A}/y^{*} = \alpha_{it}\ f(X_{it})/Max_{i}\{\alpha_{it}f(X_{it})\} = \\ = \alpha_{it}/Max_{i}\{\alpha_{it}\}$$

Formulation [3] presents the drawback that $Max_{i}\{\alpha_{it}f(X_{it})\}$ represents maximum output of the *sample*, but not necessarily of the whole population from which the sample was drawn. The (population) best practice may be "better" than that represented by $Max_{i}\{\alpha_{it}f(X_{it})\}$, thus [3] above will over-estimate efficiency levels of the firms under consideration. In many instances, however, omission of input quality as well as misspecification of the production function can counter-balance the upward bias of efficiency estimates mentioned previously.

Estimation of technical efficiency has proceeded in several directions.[2] The emphasis here will be on methods utilizing the econometric approach, which provides three alternatives for the estimation of *TE*: (i) firm-specific dummy variables (the so-called "fixed effects" model), (ii) the random-effects-effects model and (iii) the production frontier model. In this paper, particular attention will be given to the fixed-effect (dummy variable)

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[2] For up-to-date summaries see Fried, Knox Lovell and Schmidt (1993) and Cornwell and Schmidt (1996).

approach.

As a variant of [1], consider the stochastic specification:

$$[4] \quad Y_{it} = \alpha_i \ f(X_{it})\, exp(\epsilon_{it})$$

where ϵ_{it} represents the (random) impact of excluded variables. Log-linear OLS estimation of [4] will result in firm-specific intercepts, α_i, and hence of the impact of management, *M*. This formulation was originally proposed by Mundlak (1961) as a way of reducing problems caused by omission of unobserved variables, in particular management. It must be borne in mind, however, that the estimated α_i's will reflect not only *M*, but inter-firm variations in (unobserved) fixed factors as well. This will occur because in general each decision-maker manages a single unit, characterized by a given "quality" of production resources.[3]

Allocative (Cost) Efficiency: Firms may be technically efficient but economically inefficient if either: (i) input ratios do not correspond to those on the firm's expansion path, (ii) short-run Marginal Cost does not equal output price, and (iii) scale is other than that minimizing Average Total Cost.[4] Focus here will be on items (ii) and (iii), or respectively *Short-Run Cost Efficiency* and *Short-Run Profit Efficiency*.

Let $X_i^*(w,\ y^A)$ and $X_i^a(y^A)$ denote respectively a cost-minimizing and the actual input vector of the *i-th* firm used to produce output level y^A, facing input prices *w*. Also, let y^A represent the actual level of output chosen by the firm. Short-run cost efficiency (CE_{SR}) is expressed as:

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[3] If input quality is accurately accounted for it will be of no consequence for the estimation of each α_i. However, in real-world processes input quality is imperfectly measured, moreover the management input *M* will generally be (positively) correlated with the quality of inputs *X*. Neglect of this fact will cause underestimation of efficiency levels of producers in a sample.

[4] Perfectly elastic product and factor markets are assumed.

$$[5]\quad (CE_i)_{SR} = [X_i^{*} . w] / [X_i^{\wedge} . w]$$

That is, cost efficiency is the ratio of minimum cost to actual cost necessary to produce a given level of output. Cost efficiency thus measures the extent to which the input combination chosen by the firm differs from that implied by the expansion path.

Allocative (Profit) Efficiency: Denote by $C(w,\ y^{A};\ Z)$ the minimum variable cost of producing output y^{A} given input prices w and an endowment of fixed factors Z. As before, output level Y^{A} represents the actual output chosen by the firm. Further, denote $C(w,\ y^{*};\ Z)$ minimum cost of producing output y^{*}, where y^{*} is such that marginal cost equals product price: $\partial C(y;\ Z)/\partial y = p$. Short-run profit efficiency (PE_{SR}) is defined as:

$$[6]\quad (PE_i)_{SR} = [p\ y^{A} - C(w,\ y^{A};\ Z)] / [p\ y^{*} - C(w,\ y^{*};\ Z)]$$

Note that PE refers to loss of profit due to a non-optimal output level, once both technical as well as cost inefficiencies have been purged out. This loss of profit is lower than the overall loss in profit that the firm suffers from all sources of inefficiency combined. A further caution in interpreting [6] is that risk-aversion or financial constraints may result in $y^{A} < y^{*}$ and thus $PE < 1$. That is, the profit function $\pi(y) = p\ y - C(w,\ y;\ Z)$ may be sufficiently "flat" so as to imply that sub-optimal values of y are "nearly as good" as y^{*}.[5]

Optimal input ratios vary from one period to another due to variation in price ratios w_i/w_j. Input ratios should be changed if the benefits implied in producing on the expansion path outweigh adjustment costs. Failure to minimize costs may thus reflect both "hidden" adjustment costs, as well as managerial limitations in discovering and acting upon new incentives (prices).

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[5] This issue is important for industries (e.g.agriculture) characterized by production variability and few opportunities for risk-spreading through formal capital markets.

For profit maximization, changes in the output price will require either increased or decreased use of the input bundle, with resulting higher or lower levels of total product. Given the time-lags of most production processes, it should be expected that $CE > PE$. Indeed, optimal input combinations require information on current price ratios, while optimal output decisions require information on input prices paid now and output prices to be received in the future. That is, achieving $PE = 100\ \%$ requires accurate forecasting of future prices, while $CE = 100\ \%$ only requires alertness to changes in current prices.[6]

III. A Case-Study

Panel data sets appropriate for efficiency estimation are not easy to come by. This is particularly true in Argentina, where micro-level research is still infrequent. The example to be analyzed here relates to the agricultural sector. A summary of characteristics of the firms to be analyzed is presented in **Appendix A.**

A Cobb-Douglas production function is used to represent production technology of a set of 32 firms for which records for 5 or more years are available. The Cobb-Douglas function was chosen because of ease of estimation, the limitations implied by this function (in particular, elasticity of substitution equal to 1) are deemed not crucial for the results. Restricting the sample to firms with records for half a decade or longer should allow more accurate inferences to be made on the different dimensions of efficiency.[7] The model to be estimated is:

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[6] The above is strictly true for situations where prices cannot be locked-in by the use of futures markets.

[7] A longer time period allows both (i) more accurate estimates of β, as well as (ii) more observations (and between-year variability in prices) for estimation of allocative efficiency.

[7] $y = \alpha \ exp(\lambda t) \ X_1^{\beta 1} X_2^{\beta 2} X_3^{\beta 3} X_4^{\beta 4} X_5^{\beta 5}$

where t represents the time-period (1985-1993) and allows the possibility of neutral technical change, and the X_i's represent production inputs (land, overhead expenses, biological capital, direct expenses and labor). The fixed-effects model incorporates firm-specific dummies to [7] above:

[8] $y_i = \alpha_i \ exp(\lambda t) \ X_1^{\beta 1} X_2^{\beta 2} X_3^{\beta 3} X_4^{\beta 4} X_5^{\beta 5}$

Table 1 shows econometric results for both the OLS as well as the fixed-effects estimation methods. The following observations can be made on the results:

(1) A test statistic comparing the OLS with the fixed-effects panel data model suggests that the former should be rejected in favor of the latter. Indeed, the corresponding F-value comparing the fixed-effect and the model including only X variables is 4.909, significant at $p = 0.005$. For the fixed-effects model, the following comments apply:

(2) The time-trend (neutral technical change parameter) is significant ($p = .05$). The implied rate of neutral technical change is similar to those found in the literature (e.g. see Capalbo and Antle, 1988).

(3) The variable for overhead expenses is non-significant; however all other variables are significant. The labor variable presents the lowest significance levels; the land, biological capital and production expenses variables presenting t-values that are considerably higher.

(4) The test of hypothesis of constant returns to scale can be rejected in the fixed-effects model. The resulting function coefficient is 1.066. Plausibility of this result is strengthened by the fact that panel-data

Table 1: Estimation Results

	OLS	Fixed Effects
Intercept	7.24	Firm-Specific
	(0.56)	
Time trend	- 0.003	0.019
	(- 0.40)	(2.75)
Land	0.055	0.529
	(1.07)	(3.79)
Overhead Expenses	0.043	- 0.011
	(1.31)	(-0.30)
Biological Capital	0.554	0.360
	(9.02)	(4.55)
Direct Expenses	0.206	0.113
	(7.64)	(3.72)
Labor	0.066	0.086
	(1.51)	(1.84)
Adj-R^2	0.918	0.948
n	223	223

procedures were used.[8]

IV. Efficiency Estimation

Technical efficiency levels were estimated using [3] above. That is, *TE* for the *i-th* firm is expressed as the ratio between the firm-specific intercept, α_i and the largest intercept in the sample, $\alpha_{max} = Max_i\{\alpha_i\}$. Preliminary results indicated that *TE* estimates were considerably lower for firms located in one of the three production areas covered by the sample ("Zone 3"). This occurs because *TE* estimates capture not only "management", but also firm-invariant (and unmeasured) characteristics associated with inputs. An attempt was made to correct for this bias by regressing *TE* estimates on an intercept and a dummy variable taking the value of 1 for firms located in the less-productive region.[9] Regression results indicate that the drop in *TE* associated with Zone 3 was 17.5 percentage points (t-value = - 10.81). Therefore, all first-round estimates of *TE* for Zone 3 were increased by this constant in order to obtain an approximation to management-induced *TE* levels. These "corrected" *TE* values are labelled *TEIC*. **Table 2** shows *TEIC* values, as well as cost and profit efficiency estimates.

Technical Efficiency: Estimated technical, cost, and profit efficiency levels for each firm are reported in **Appendix B**. Average *TEIC* is 62 percent, which is lower that both cost and profit efficiency (averages for these are respectively 94 and 69 percent).

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[8] Returns to scale estimates obtained with cross-sectional data sets frequently present an upward bias due to omitted variables. Somewhat surprisingly, the function coefficient of the model without firm-specific dummies is 0.92, significantly different (p = .01) from 1.

[9] Lower productivity was expected *a-priori* in one of the production regions. An alternative approach would have been to include a regional dummy in the original production function [8]; however this approach is infeasible due to perfect collinearity between the regional dummy and the firm-specific intercept.

Table 2: Production Efficiency Estimates

	TEIC	*CE*	*PE*
Average	62	98	69
Maximum	100	98	97
Minimum	36	82	12
SD	12	3	22

Note: $TEIC_i = TE_i + 17.07*d_Z$ where $d_Z = 1$ if the firm is located in production zone 3

Approximately 28 percent of firms show *TEIC* values that exceed 70 percent, a minimum threshold for "adequate" efficiency levels.[10] *Cost Efficiency*: Allocative efficiency (cost and profit) was estimated on the assumption that the only variable inputs are biological capital, direct expenses and labor. The non-significance of the overhead expense variable (see **Table 1**), and the suspicion that the land input is fixed in the short run prompted this approach. Both cost as well as profit efficiency was obtained by first deriving cost-minimizing and profit-maximizing input bundles;

[10] This 70 percent value is arbitrary. It attempts to allow for the fact that estimation errors probably assign to inefficiency inter-firm variation that can be accounted for by omitted variables, error in the specification of the parametric form of the production function, etc.

subsequently using these in expressions [5] and [6] above.[11]

Cost efficiency levels appear high: average *CE* is 94 percent, with a standard deviation of only 3 percent. This finding lends empirical support to the argument presented in previously: *CE* measures should be expected to be higher than *PE* (average *PE* found here is 69 %), because of the fact that only input price rations w_i/w_j are needed for decision-making, against prices w_i/p that are needed for profit-maximization. The hypothesis of cost-minimizing behavior on the part of the producers of the sample cannot be rejected.[12]

Profit Efficiency: Average *PE* level is 69 percent. Variation in *PE* as measured by the standard deviation is greater that of either *TEIC* or *CE*. Approximately 56 percent of the firms present a *PE* value equal or greater than 70 percent, the (arbitrary) efficiency threshold discussed earlier.

Estimated ratios of VMPs to input prices (*VMP/w*) suggest shadow prices used by decision-makers. For the three inputs for which allocative efficiency was calculated, these ratios are 1.13 (biological capital), 0.89 (direct expenses) and 1.31 (labor). Under the assumption of an opportunity cost of 15 percent (as used in the calculations of *PE*) these figures suggest overutilization of direct expenses and underutilization of labor. A 13 percent return on biological capital could indicate either (a slight) overutilization of this input, or simply that the shadow price used

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[11] First-order conditions for cost minimization and profit maximization provided simultaneous equations that were linearized by taking logs and then solved by matrix algebra. This, as well as the econometric estimation, was done with the LIMDEP package.

[12] Formal test of this hypothesis would involve comparing average *CE* of the sample with the (maximum) level *CE* that is possible: 100 percent. However, an average *CE* of 94 percent suggests that input combinations generally correspond to those on the firm's expansion path.

for planning is less than 15 percent.[13]

Analysis of the *VMP/w* ratio is particularly important for the biological capital input, as rough calculations indicate that this factor accounts for two-thirds to three-fourths of total variable costs (biological capital + direct expenses + labor). **Figure 1** shows relative frequency of this ratio. Three-fourths of observations present (100*[1-*VMP/w*]) ratios in the 10 - 15 percent range, a figure that is probably in the same ballpark as interest rates charged to creditworthy firms. It should be recalled that these *VMP/w* ratios reflect *ex-post* results from decisions; in this context the relatively tight grouping of the ratio around hypothesized opportunity costs suggests care in resource allocation on the part of decision makers.

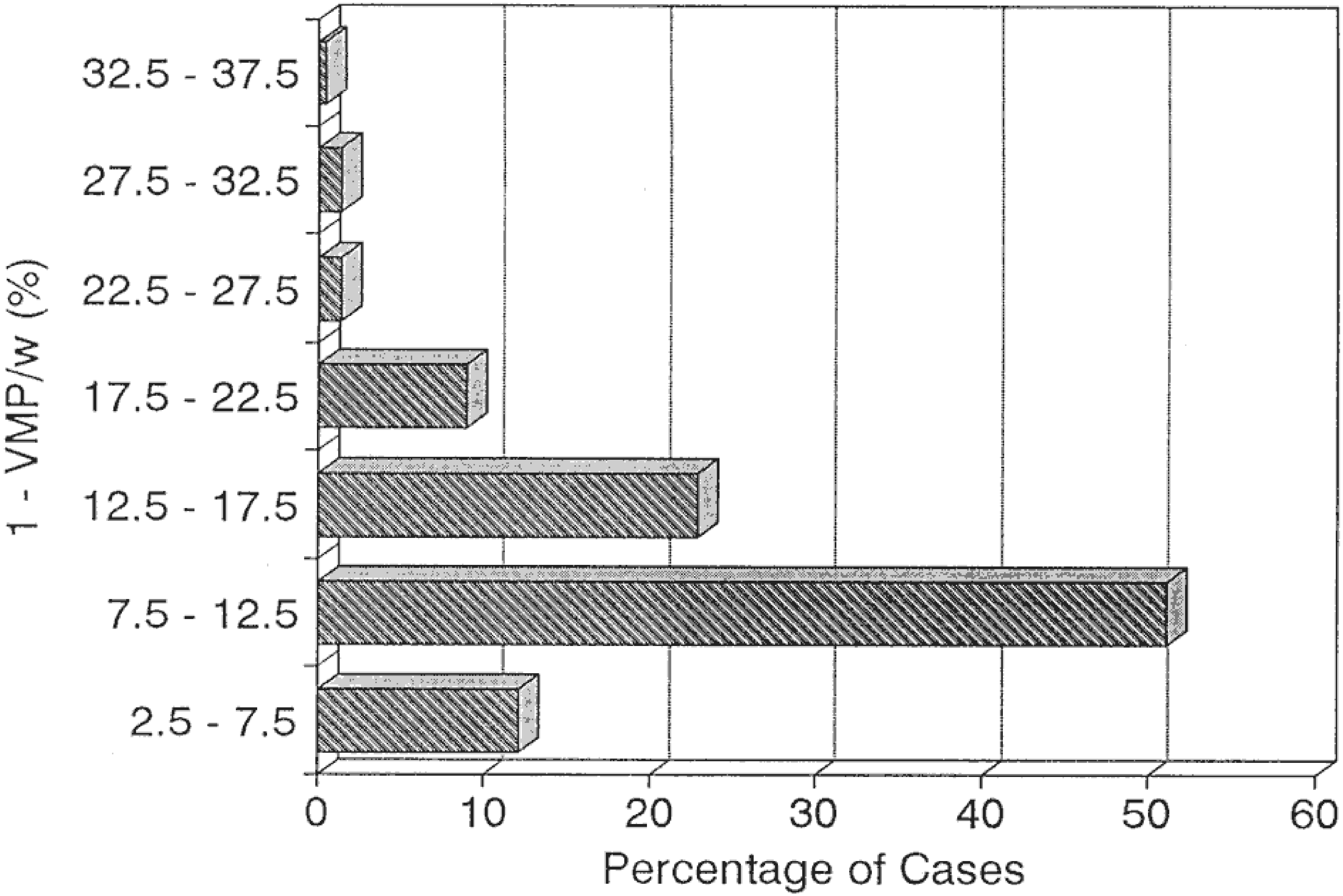
V. Additional Results

A further issue merits attention. If efficiency estimation is to be of value for decision-makers, attention should be directed to the factors responsible for inter-firm differences in performance. A simple model to be tested is that efficiency (be it technical, cost or profit) depends on the complexity of the firm's production processes, on the prevailing uncertainty of the factor and product markets in which the firm operates, and on the quality of the human resources that are available. The above factors include both demand for as well as supply of decision-making inputs.

Proxies can be devised to approximate the above factors. For firms with similar technologies, size is a reasonable approximation to the burden posed by coordination. "Size" will refer here to the quantity of the most important input (land) that these firms use.

[13] Firm-specific costs of capital are notoriously difficult to estimate. Some evidence (Nava, 1997) suggests that in the Argentine agricultural sector firms faced in the early 1990s interest rates of approximately 20 percent. Large firms such as analyzed here, however, conceivably have better access to both risk as well as debt financing.

FIGURE 1: VMP/w Ratios
Biological Capital Input (X3)



Prevailing uncertainty will be proxied by a dummy variable taking a value of 1 for periods with high inflation, and 0 for periods when inflation was low and decreasing. The Argentine economy provides an interesting experiment for this issue: in 1991 macroeconomic reforms resulted in a virtual elimination of inflation, a dramatic contrast to the situation prevailing during the 1980's, when annual price increases were among the highest in the world. The sample for firms covers the 1985 - 1993 period; hence the uncertainty dummy takes a value of 1 in years 1985-1990, and a value of 0 otherwise. Lastly, quality of human resources should ideally be measured by a composite index that takes into account education as well as experience of both managers and workers. Information is not available to construct such an index. Therefore, average annual salaries paid by the firm is taken as a proxy of the decision-making inputs embedded in the workforce.[14]

Regressions were run expressing technical, cost and profit efficiency as a function of the three variables mentioned above. Results were disappointing: the size variable was (statistically) associated with greater technical and profit inefficiency; however results were reversed for cost efficiency. Estimated coefficients were in all cases small: plausible increases in size resulted in an increase (or decrease) of efficiency that was less than 0.5 percentage points. Inconclusive results were also obtained for the worker quality proxy. Finally, the inflation dummy was in all cases non-significant.

VI. Conclusions

This paper presents an estimation of a firm-level production function, as well as of technical, cost and profit efficiency values. Results are generally plausible. It must be recognized, however, that the data-set used here includes a lengthy period of

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[14] Wage differences can be interpreted as differences in worker quality.

observation (up to nine years) of individual firms. Such data will generally be gathered as a by-product of efforts made by accountants or management consultants; researchers will seldom have the time or the resources available for widespread application of similar procedures.

Are the firms in the sample efficient ? One would expect definite answers to this question, considering the use of relatively sophisticated methodology, as well as of a detailed, micro-level data set. The answer, however, appears ambiguous. Cost efficiency values are close to 1. Profit efficiency appears relatively high, given the uncertainties involved in predicting future prices and input productivities. Technical efficiency, however, seems to be lower than would be expected of a relatively homogeneous sample such as used here. This could indicate learning lags, hidden costs in using some practices, or (more likely) errors in the measurement of input or output variables.

The issue of the impacts of inflation on firm level production efficiency deserves greater attention. Future studies should also gather data pertaining to the skill level of the decision-maker (formal education, experience, etc). Lastly, future studies should attempt to correlate econometric estimates of production efficiency with those resulting from subjective evaluations from individuals knowledgeable of the industry under study.

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Appendix A: Sample of Firms

Firms analyzed in this paper belong to the agricultural sector. Firms are located in three contiguous production regions of the Province of Buenos Aires (Zone 1 = North, Zone 2 = West, Zone 3 = Southwest). The firms are considerably larger and (probably) better managed than those in their respective areas. All employ part-time consultants. One of the regions ("Zone 3") presents production conditions of less potential than the other two. Inputs and outputs used to fit the production functions pertain to the livestock enterprise of these firms. The following description corresponds to variables used in estimation:

Y = output (kg beef)

t = time trend t= 1985, 1993

X_1 = land (hectares)

X_2 = overhead expenses (Argentine $, August 1993)

X_3 = biological capital (livestock average inventory, kg)

X_4 = direct expenses ($)

X_5 = labor (man-equivalents)

Appendix B: Firm-Specific Efficiency Estimates

Firm #	# Periods	TEIC	CEF	PEF
1	6	.709	.970	.886
2	7	.585	.952	.485
3	6	1.000	.891	.970
4	9	.635	.936	.429
5	8	.675	.928	.973
6	9	.778	.887	.864
7	7	.530	.938	.840
8	7	.703	.956	.883
9	7	.649	.912	.864
10	7	.441	.972	.829
11	5	.674	.877	.952
12	7	.359	.822	.441
13	5	.477	.954	.578
14	5	.355	.944	.669
15	5	.738	.975	.679
16	5	.593	.967	.401
17	8	.730	.930	.837
18	6	.762	.919	.928
19	8	.750	.948	.849
20	6	.580	.984	.457
21	6	.603	.917	.465
22	9	.591	.969	.467
23	6	.615	.969	.755
24	6	.600	.962	.795
25	5	.581	.975	.300
26	7	.667	.947	.767
27	9	.603	.937	.783
28	9	.530	.982	.124
29	7	.708	.939	.915
30	9	.595	.976	.820
31	8	.574	.964	.602
32	9	.623	.953	.502