



Returns to Managerial Ability and Technical Efficiency in Argentina Dairy Farms

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Abstract:

This paper explores the returns to managerial ability and his role in determining efficiency in Argentina dairy farms. Using an unbalanced panel data from 2003 through 2009 we estimate production frontiers and technical efficiency effects. Most studies analyzing the impact of human capital in agriculture use the measure of years of schooling of the producer as a proxy for decision-making skills. An alternative measure is used in this paper. The measure was derived by “grading” decision-making and execution skills of the farmers. Grades were assigned by farm advisors knowledgeable of each farm and producer characteristics. Assigned grades were then used in the production frontiers as inputs to estimate the impact of management skills on firm-level results. A very significant impact of these skills on firm results and on technical efficiency and was found.

Acknowledgment:

JEL Codes: Q12, D22

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Introduction

New technologies, changes in relative prices and changes in the factor and output markets faced by farmers have resulted in a substantial increase in the demand for decision-making skills. As pointed out by Schultz (1975) these skills can be considered an “ability to deal with disequilibrium”. It is these changes (disequilibrium conditions) that place a premium on transforming data and other signals into useful information, and this information into purposive, goal-oriented action. Variation in managerial skills will give rise to variation in firm-level outcomes.

Research carried out since the early 1970’ has shown that farmer education is an important variable explaining input use (Huffman, 1977), firm efficiency (Fane, 1975), off-farm labor allocation (Huffman, 1980) and other aspects. Farmer education is seen as particularly critical in low-income countries where a large portion of total population is employed in agriculture, educational levels are low, and new technologies place considerable demands on production management. Studies analyzing the impact of human capital on production efficiency have distinguished between a “worker” and an “allocative” effect (Welch, 1970). The former relates to education allowing more output to be obtained with the same input level. In turn, the latter results from improved decision-making abilities allowing adaptation to change. More recent studies have in general confirmed and extended previous results (for a summary see Huffman 2000).

Years of formal education are only a proxy for the farmer’s ability as a manager. In particular, learning-by-doing, participation in farmer groups, community networks and extension services can all complement or substitute the farmer’s educational level in generating decision-making outcomes. Herbert Simon and colleagues (March and Simon, 1958) pointed out several decades ago that the “logic of consequences” (“rational” appraisal of alternatives) may be of less importance than the “logic of appropriateness” whereby courses of action are recalled from rules of thumb that were helpful in previous instances. More recently, Vernon Smith (2008) argues that “ecological” rationality (rationality resulting from situation-specific adaptive behavior) may be more useful than “constructivist” rationality, where actions are chosen on the base of some type of means-ends prediction.

The above points out that learning-by-doing and “on-hands” experience may explain an important part of productivity differences between firms. The concept of “human capital” should then include not only formal “classroom” learning, but other forms of knowledge uptake as well. This is particularly important when attempting to explain differences in performance of medium or large-sized farms, where most if not all entrepreneurs have completed high school, many of which have also attended the university. For these farmers differences in “managerial human capital” may have more to do with aspects such as previous experience, the “need for achievement”, overall managerial approach and other factors, than differences in the formal level of education attained.

Nuthall (2009) uses micro-level data to test the hypothesis that previous experience, “management style”, personal objectives and other factors affect managerial ability. The point made is that in some situations differences in “decision quality” are not primarily a function of differences in formal schooling (as for medium/large farms these differences are small or nonexistent) but of a set of variables reflecting hands-on experience, individual objectives and other aspects. Heterogeneity is thus an important characteristic to be taken into account when analyzing performance of farm firms.

In a recent paper Byma and Tauer (2010) explores the role of managerial ability in explaining efficiency in a group of New York dairy farms using stochastic distance frontier functions. The main hypothesis of the paper is whether inefficiency is due to measures of managerial ability, a possible missing input in efficiency measurement. They use lagged net farm income and farmers’ own estimates of the value of their labor and management as proxies for managerial ability, finding significant positive impacts on efficiency. Efficiency also increases with operator education, farm size, and extended participation in a farm management program.

This paper has the objective of estimating the impact of managerial ability on production efficiency and firm results. Managerial ability is not measured here by years of schooling as is common in most human-capital studies in agriculture but by third-party assessment of how management carries out tasks. Task performance – the direct result of managerial action – is then a basic input into the production process. This input’s productivity is analyzed here.

Assessment of each farm’s managerial “quality” was made by the farm’s professional advisor. These assessments were used to predict the impact, on farm production and efficiency, of improving decision-making and executive skills.

The paper attempts to quantify the value of efforts aimed at improving overall managerial effectiveness. Effectiveness scores used here are thus not derived from “input” measures such as years of schooling, but from direct observation of managerial behavior on a day-to-day basis. The existence of a positive relation between (subjective) managerial effectiveness scores and “objective” firm outcomes – if confirmed – has several implications. First, selected decision-making skills can be linked to observed firm performance. This can allow improved tailoring of educational and extension programs to farm-level demands. Second, the fact that effectiveness scores are derived from (subjective) farm advisor diagnosis suggests that advisors themselves have valuable knowledge on the determinants of production efficiency. How this knowledge is translated into improved performance is an issue worth attending.

The hypothesis to be tested is that managerial ability measures have predictive value in explaining farm output. This hypothesis is non-trivial, as the possibility exists that “grades” (managerial effectiveness scores) assigned to managers will not be related, or be only weakly related, to production efficiency. For example, advisors may be “production oriented”, placing emphasis on increased input use and output maximization, and not necessarily on efficiency per-se. Production specialists may also in some cases overrate the impact of certain “fashionable” practices, and underrate producers who choose more modest but equally efficient approaches.

It is also possible that in the group of farms analyzed here the role of the private advisor is be more of a “facilitating” (networking, information transfer) than pure “consulting” type – i.e. the advisor does necessarily “know more” than his client, his role being in helping his client in exploring production and management alternatives.¹ If this is the case, advisor assessment of managerial quality will not necessarily be correlated with differences in firm performance. Indeed, only if “knowledge gaps” exist between farm advisors and what is done at the farm level (advisors having identified problems or opportunities not identified, or not acted upon by farm owners) will advisor evaluations signal performance differences among farms.

Managerial know-how and farm efficiency

¹ Farms advisors may play other roles as well. For example, in farms where partial or total separation exists between management and control, advisors may act as production and management (informal) “auditors” improving control by owners. See Gallacher, Goetz and Debertin, (1994).

Monitoring input contribution and allocating rewards and punishments is a basic managerial function (Alchian and Demsetz, 1972). This function is carried out directly by owners in owner-controlled firms or by professional managers in firms where ownership is separated from day-to-day control. In these “corporate” firms additional delegation problems emerge.

The standard production function approach abstracts the monitoring and management function as described above, and managerial ability is a “missing variable” in most of the econometric specifications. Broad categories of inputs are combined in order to produce certain output. In a real-world firm, of course, many different sub-production processes take place simultaneously or in sequence. The efficiency with which inputs are transformed into intermediate and final outputs depends on how well these numerous sub-production processes are carried out. For example, in a dairy farm the efficiency with which pastures or concentrates are transformed into milk depends on a number of day-to-day decisions. Similarly, effective labor management practices may allow result in more “effort” to be obtained from a same amount of nominal labor-hours. Leadership skills, in particular, may be important for teamwork to develop. The effectiveness of the Alchian and Demsetz “monitor” may well vary among firms.

The extent to which managerial skills are applied in the production process may be gauged by knowledgeable observers. Extension workers, farm advisors, consultants as well as successful farmers may all be capable of “grading” application of management know-how in a given farm. The degree to which the assigned “grade” predicts production efficiency will of course depend on several factors. Of these, the skill of the observer and the frequency with which the graded farm is visited by this observer appear to be particularly important. Assigning “grades” to managers on the basis of observation of on-farm practices is conceptually no different from assigning grades to students in the sense that assigned grades may or may not be correlated with the underlying output of interest -- production efficiency in the case of a farm, “labor market success” or other outcomes in the case of a student.

The above raises the question of the reason behind the “performance gap” existing between “how well things are carried out” and “how well they could be carried out”. For example, why farmer *A* scores low on the item “pasture production and utilization” or on “attitude to change”. In a conventional microeconomic framework, the only possible explanation for the “low score” is that changing this score to a higher one would not be profitable: i.e. the resulting increase in revenue is less than the change in cost necessary

for the score increase. For example, an older farmer may find the benefits of “changing his ways” small (he will retire in a few years) while the costs of doing so are “large” (he values his leisure highly).

Alternative explanations may include aspects such as “satisficing” behavior (which in a sense is not at odds with the conventional approach once all relevant costs are taken into account), aversion to risk (or “change”) or other factors. Whichever is the case, both practitioners as well as research results (see e.g. Bravo-Ureta, 2002) point out that production efficiency in many firms is well below the maximum possible.

As a first approximation, the following two-way classification of managerial inputs is presented:

1. Production management: this dimension focuses on “practical” aspects. For example, pasture and supplementary feed management, labor quality and supervision.
2. Leadership and entrepreneurial function: includes “intangibles” such as focus on the business, general managerial know-how, leadership skills and attitude to change.

Positive correlation is expected between items 1 and 2 above. However, informal evidence suggests that some managers may excel in some function but achieve modest results in another. In particular, “production-oriented” managers may focus attention on “nuts and bolts” aspects such as efficiency of the grazing system, or the throughput of the existing milking shed, and neglect “business” aspects such as the need for new investments or of renting additional land. Further, improving items 1 and 2 may require different approaches. In particular, practical demonstrations may be extremely useful in order to reduce (say) losses in administering silage to cattle; however “blackboard” instruction may be necessary is business planning or even leadership skills are to be improved.

The Case Study

We analyze firms belonging to the Argentine agricultural sector. Records of dairy farms were used to estimate the impact of managerial know-how on production. Data on output and input used was obtained from detailed records kept by farm participating in the

Argentine CREA (“Consortios Regionales de Experimentación Agrícola”) groups. The CREA movement started out in Argentina in the late 1950’s. It’s focus is to develop and help spread improved agronomic, livestock production and general management technologies at the farm level. CREA farms also carry out applied agricultural systems research. Some 200 groups of 10-12 farms each comprise the organization. Each of these groups hires a part-time professional advisor/facilitator and meets regularly (at least once a month) to discuss ways to improve efficiency. The advisor is not expected to deliver “consulting” services in the traditional sense but to facilitate learning and the transfer of information. CREA group members learn both from themselves as well as from other farmers. Comparative analysis of production records provides additional insights related to the possibility of improvements.

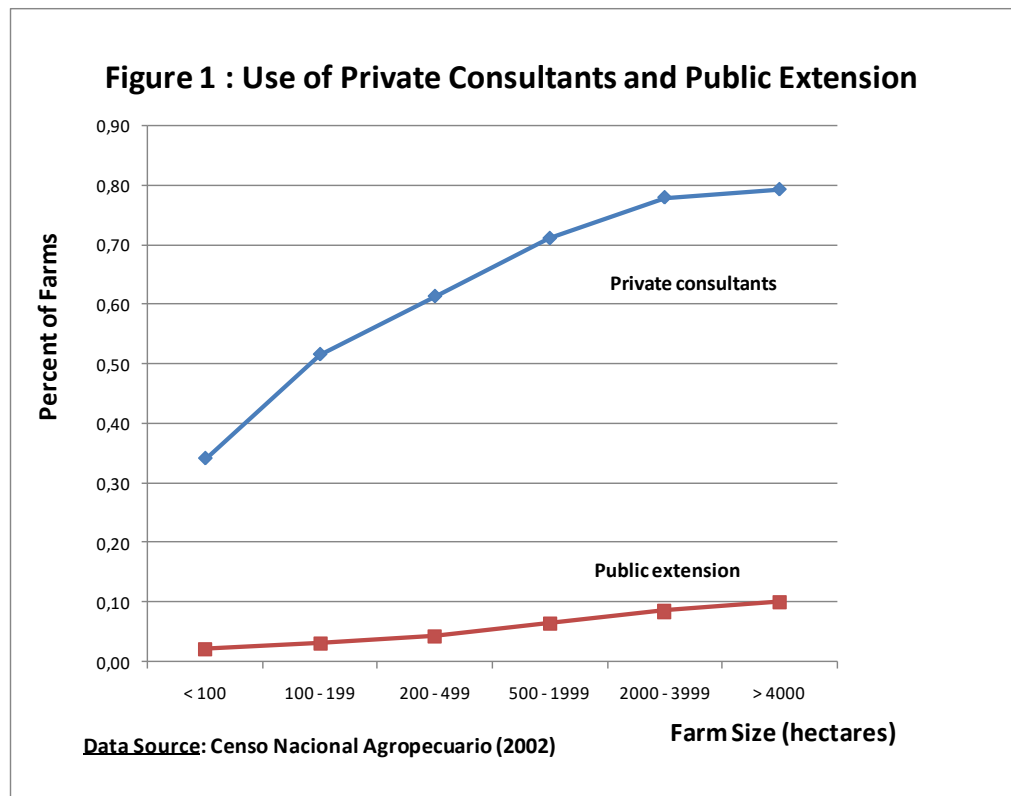
Table 1. Description of Farms

Production Area	Farm Size (hectares)	Herd Size (milk cows)	Supplementary Feed (tons grain equivalent)	Labor (full-time equivalent)	Output (millon litres milk)	Land Rental* US\$/ha
Centro	228	278	1351	4.3	2.1	370
Este	262	373	1336	4.7	2.3	285
Lit Sur	327	372	1149	2.9	2.3	237
MyS	296	385	1409	5.5	2.2	219
NOA	343	533	2203	9.8	2.4	170
Oeste Aren	514	734	2828	9.5	4.8	267
Oeste	299	390	1694	4.5	2.5	333
Sfe C	134	205	665	2.7	1.2	333
SSFe	804	1024	4717	10.3	7.0	315
All	293	383	1517	4.7	2.4	300

(*) Land rental value: average (estimated) rental value for the 2010 year

CREA can be considered a privately-sponsored “agricultural extension” organization. In Argentina delivery of production and management information is done

primarily by private-sector professionals. As shown in Figure 1, farm use of private advisors and consultants increases from some 30 - 40 percent for farms of less than 100 hectares, to 80 percent in farms larger than 4000 hectares. In contrast, public-sector extension services reach less than 10 percent of farms of all size classes. The importance of privately employed professionals in information delivery suggests that these professionals are a significant source of know-how. We address below the issue of the predictive value of this knowledge.



Each farms' management "quality" was assessed by the farms' advisor. Only one "management grade" was assigned per farm, independent of the number of years of records available for the farm (this assumes for the farm unchanging "management quality" through time). Some 200 farms were assessed. More than one year of data is available for most farms, resulting in a data base of 500 observations. Assessment includes items ranging from "practical" aspects such as grazing efficiency and the management of milking operation to more "general" variables such as leadership, business focus and adaptation to change. Following the discussion of the previous section, two management-quality indexes were derived from the questionnaire: (i) the Production Management Index and (ii) the Leadership/Entrepreneurial Index (respectively the PMI

and LEI). Both of these indexes are simple arithmetic averages of production- and “management” scores received by the farmer from his professional advisor:

$$(1)PMI_i = 100 * [fm_i + sfm_i + l_i]/15$$

$$(2)LEI_i = 100 * [bf_i + le_i + tr_i + ch_i]/20$$

Where, for the *i-th* farm (management scores take integer values of 10 [bad], 20 [deficient], 30 [good], 40 [very good] and 50 [excellent]):

fm_i = forage management

sfm_i = supplementary feed management

l_i = labor management/quality

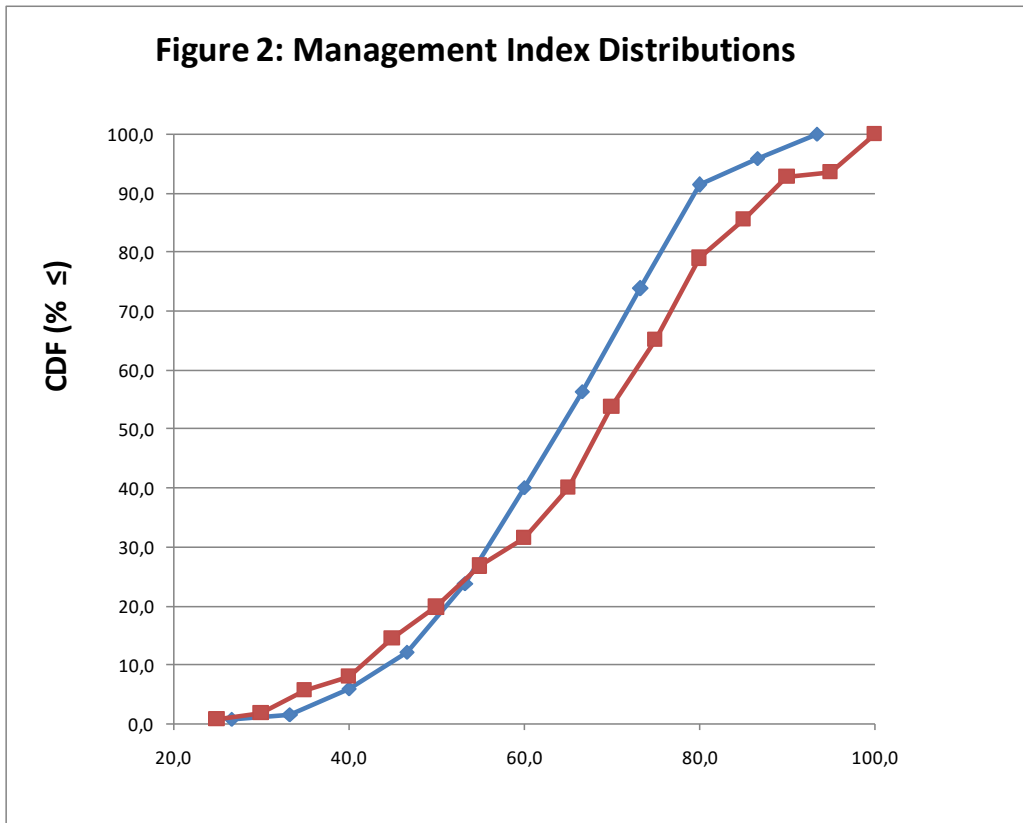
bf_i = business focus

le_i = leadership

tr_i = managerial training

ch_i = attitude to change

Figure 2 shows the cumulative distribution function of both indexes. “Sparse-data” procedures (Anderson, Dillon and Hardaker, 1977 p. 40) were used to construct CDF’s. In a 0-100 scale the median value is approximately 65 for the PMI and 70 for the LEI (for both indexes the median values are somewhat higher than “good”). A substantial portion (> 20 percent) of the sample has management indexes below 50; conversely 10 – 20 percent of the sample has indexes above 80. The variability of the LEI appears larger than that for the PMI. This opens the possibility of substantial improvements in overall efficiency by focusing educational programs on issues such as leadership, managerial decision-making and teamwork.



Production Function and Technical Efficiency

The following Cobb-Douglas function is used to estimate resource productivity and returns to improving managerial quality:

$$(3) y_{it} = \exp(A + \sum \gamma_j D_j) H_{it}^{\beta_1} C_{it}^{\beta_2} SF_{it}^{\beta_3} L_{it}^{\beta_4} OE_{it}^{\beta_5} PMI_i^{\beta_6} LEI_i^{\beta_7}$$

where:

y_{it} = output (milk)

H_{it} = land (total land rental imputed value)

C_{it} = herd size (cows)

SF_{it} = supplementary feed (tons grain equivalent)

L_{it} = labor (full-time equivalent years)

OE_{it} = overhead expenses (pesos)

PMI_t = production management index

LEI_t = leadership entrepreneurial index

First, we choose a conventional production function and the model presented in equation (3), where managerial inputs enter directly in the production process, is estimated by OLS. Second, we estimate the same production function using stochastic frontier models. The inclusion of proxies for managerial inputs in a stochastic frontier implies that the estimated technical inefficiency effects captures other constraints on the use of know-how, different from managerial ability. These constraints are considered as a random effect and modeled as a stochastic element of the production function.

Table 1 describes the sample of farms. Most farms are located in the *pradera pampeana* (pampean prairie), a highly productive grain-livestock area. Average farm size is nearly 300 hectares, considerably (some 50-70 percent) larger than the average of dairy farms in the country. As mentioned previously, these farms belong to a farm-management association, and as such can be expected to attain efficiency levels above those reached by the average dairy farm.

As relates to managerial practices, 91 percent of farms are owner-managed, and in 44 percent of farms the manager engages in other activities besides managing his farm. In these farms labor inputs are not provided by the manager but by hired workers, overall “production” supervision being frequently carried out by a hired foreman, in some cases paid partially or totally by a piece-rate system. The manager then makes overall input allocation decisions, purchases inputs and negotiates output sales, maintains production and financial records.

Estimation results are shown in Tables 2 and 3. Table 1, column 1 presents the basic OLS estimates. With the exception of overhead expenses all “conventional” input variables are significant ($p=.01$). “Managerial expertise” variable *PMI* is significant at $p = .01$, variable *LEI* are significant at $p = .05$. This indicates that advisor perceptions (or diagnosis) of management quality has predictive value. Partial elasticity of output with respect to the *PMI* (0.11) is higher than that of the *LEI* (0.08).

“Technical Efficiency” (TE) in this case is defined as the ratio “actual” to “potential” output. For the sample of farms analyzed here it can be computed using the estimated production function. “Potential” output is represented by that attained by the producers in the 90-percentile management level. Under these assumptions, median TE then results (refer to Figure 2 for the median and 90-percentile index values):

$$(4)TE (\%) = 100 * \frac{[60^{0.11} 65^{0.08}]}{[80^{0.11} 90^{0.08}]} = 94.4$$

Table 2. Production Function (OLS) and Stochastic Frontier Estimates

Variables	1		2		3	
	Coeff	t	Coeff	z	Coeff	z
<i>Constant</i>	-1.01	-5.22 ***	-0.95	-5.19 ***	-1.08	-5.25 ***
<i>H (land)</i>	0.08	3.51 ***	0.09	4.33 ***	0.10	4.03***
<i>C (herd size)</i>	0.59	17.91 ***	0.56	18.03 ***	0.59	18.65 ***
<i>SF (supplementary feed)</i>	0.11	5.55 ***	0.11	6.32 ***	0.11	5.89 ***
<i>L (labor)</i>	0.22	10.22 ***	0.22	10.80 ***	0.21	9.76 ***
<i>OE (overhead expenses)</i>	0.01	0.71	0.01	1.01	0.008	0.89
<i>PMI (management index)</i>	0.11	2.85 ***	0.11	2.69 ***	0.11	2.47 **
<i>LEI (leadership index)</i>	0.08	2.10 **	0.08	2.35 **	0.09	2.28**
σ^2			0.033	9.387 ***	0.015	13.63 ***
γ			0.615	8.473 ***	0.99	100 ***
Adj. R ²	0.96					
Observations	499		499		499	
Number of farms	180		180		180	
log likelihood	262.739		271.692		280.18	
LR Test			17.91		34.89	
Df			1		1	
Average Efficiency			0.90		0.93	
Estimation Method	OLS		Stochastic Frontier. Pooled data (Aigner et al 1977)		Time Invariant Stochastic Frontier. Panel data (Battese and Coelli, 1988)	

Dummy variables not reported.

(*), (**), (***) significant at 10%, 5% and 1% respectively.

LR test: One-sided Generalised Likelihood-Ratio Test.

Table 3. Stochastic Frontier Estimates

Variables	1		2		3		4	
	Coeff	z	Coeff	z	Coeff	z	Coeff	z
<i>Constant</i>	-0.34	-1.72 *	-1.01	4.86 ***	-1.08	-5.12***	-0.91	-4.84***
<i>H (land)</i>	0.02	1.07	0.10	4.17 ***	0.11	4.86***	0.091	4.19***
<i>C (herd size)</i>	0.74	23.51 ***	0.56	16.78 ***	0.56	19.16***	0.56	19.08***
<i>SF (supplementary feed)</i>	0.08	4.29 ***	0.11	5.14 ***	0.12	7.03***	0.11	6.63***
<i>L (labor)</i>	0.16	7.35 ***	0.23	10.15 ***	0.20	10.17***	0.25	12.27***
<i>OE (overhead expenses)</i>	0.01	0.62	0.01	1.23	0.007	0.82	0.005	0.60
<i>PMI (management index)</i>	0.08	1.74 *	0.06	1.23	0.10	2.26**	0.07	1.69*
<i>LEI (leadership index)</i>	0.03	0.75	0.10	2.42 **	0.08	2.12**	0.09	2.51**
<i>Trend</i>			0.02	3.37 ***				
<i>Innefficiency Effects-Col. 1</i>								
<i>Constant</i>	7.24	4.24 ***						
<i>PME</i>	-1.48	-5.09 ***						
<i>LEI</i>	-0.95	-2.51 **						
σ^2	0.23	4.36 ***	0.32	3.64 ***	0.09	17.68***	0.11	27.34***
γ	0.96	93.93 ***	0.95	68.15 ***				
η			-0.80	-6.07 ***				
Observations	409		409		499		499	
Number of farms	180		180		180		180	
log likelihood	269.207		248.874		312.41		309.37	
LR Test	12.885		82.409					
Df	4		3					
Average Efficiency	0.93		0.96		0.93		0.92	
Avg. Efficiency year 2003			0.998		0.92		0.89	
Avg. Efficiency year 2004			0.997		0.94		0.94	
Avg. Efficiency year 2005			0.992		0.95		0.96	
Avg. Efficiency year 2006			0.985		0.94		0.96	
Avg. Efficiency year 2007			0.959		0.94		0.94	
Avg. Efficiency year 2008			0.915		0.92		0.90	
Avg. Efficiency year 2009			0.857		0.91		0.84	
Estimation Method	Tech. Eff. Effects Stochastic Frontier. Panel data (Battese and Coelli, 1995)		Time-varying Inefficiency Model. Panel Data. (Battese and Coelli, 1992)		Time-varying True Random Effects Model Panel Data (Greene, 2005)		ML random-effects flexible time-varying efficiency model (Kumbhakar, 1990)	

Dummy variables not reported.

(*), (**), (***) significant at 10%, 5% and 1% respectively.

LR test: One-sided Generalised Likelihood-Ratio Test.

Table 2, column 2 presents the results using a pooled data stochastic frontier (Aigner, Lovell and Schmidt, 1977) and column 3 the estimates of a panel data time invariant stochastic frontier (Battese and Coelli 1988). Table 3, column 1 presents the estimates of a technical efficiency effects stochastic frontier for panel data (Battese and Coelli, 1995). Column 2 presents a time-varying inefficiency model for panel data (Battese

and Coelli, 1992). Column 3 presents the True random-effects model (Greene, 2005) and column 4 the maximum likelihood random-effects flexible time-varying efficiency model (Kumbhakar, 1990).

Comparing the OLS coefficient estimates and the deterministic estimation of technical efficiency with the estimates obtained using stochastic frontier models we observe that coefficient estimates for conventional inputs and managerial inputs are similar in terms of magnitude and significance. The average efficiency effects in stochastic models range from a maximum of 96 per cent to a minimum of 90 per cent. The estimate of γ coefficient in the stochastic frontier models suggests that an important part of the residual variation is due to the inefficiency effects (u_i), and that the random error part (v_i) is close to zero in models 3 and 4. Also, according to the one-sided generalized likelihood-ratio test of $\gamma=0$, the stochastic frontier models are preferred to the traditional average response function. Both results suggest that the stochastic frontier models are not significantly different from the deterministic frontier model with no random error included.

Our estimates of production efficiency can be compared also to other similar studies, albeit with caution because of differences in the estimation procedures. For example, Bravo-Ureta (2002) provides a comprehensive summary of efficiency studies. In high-income countries (HIC) TE averages (all reported studies) range from a maximum of 97 to a minimum of 53 percent (average 80 percent). In turn, in low-income countries (LIC) TE ranges from 88 to 53 percent (average 74 percent).

The study of Byma and Tauer (2010) on dairy farms also reports high technical efficiency levels of 0.91 and 0.92, and significant positive impacts of the managerial ability measures on efficiency. These findings support the hypothesis that measured inefficiency may be due to the missing managerial ability input and are consistent with our estimates.

It is important to bear in mind that TE values found here result from a sample of farms most probably characterized by substantially higher managerial efficiency than the average farm of the country. Thus, these TE values overestimate “true” efficiency levels of the Argentine dairy sector.

Managerial Ability and Output Change

Production function results can be used to predict output change resulting from managerial improvement. Using the OLS estimates (traditional average response function), we assume here a change in the PMI and LEI from a “low” value of 50 to a “high” one of 80. These values approximately correspond to the 20 and 80 (for PMI) and 90 (for LEI) percentiles in the management index distributions (see Figure 2). The improvement in managerial ability assumed here is therefore substantial. Table 4 shows predicted output increases for several production areas. Results are expressed in US\$ and were calculated for median values of resource use in each of the reported areas.

If both *PMI* as well as *LEI* increase from the 20 to the 80/90 percentile level, predicted output will increase 9.4 percent (see Table 4). In financial terms, output loss incurred by managers graded as “deficient” as compared to those graded “very good/excellent” varies from 150 to 180 US\$ per hectare. In order to gauge the importance of these figures, a comparison can be made with average rental rates for land in the chosen production areas. As shown, these range from a minimum of US\$ 170 in the sub-tropical “NOA” area to a maximum of US\$ 370 in the “Centro” region. The output loss/land rent ratio varies from close to 1 for the NOA region, to 0.46 for the Centro region. These results are large: output losses (expressed on a per-hectare basis) can in some cases equal land rental rates.

For the farms in the sample, output differences computed at median input use levels of the 20- as compared to the 80/90-percentile management index range from 25.000 to more than 145.000 US\$ per year. These disequilibrium levels are well above what would be needed (for example) for the hiring of full-time and high-quality managerial assistance. Disequilibrium in the use of managerial inputs appears to occur: marginal productivity of managerial inputs are presumably higher than the price of these inputs.

Table 4. Impact of Improvement in the Production Management and Leadership Entrepreneurial Indexes (PMI & LEI) by Farm Region

	Production Increase (%)	Centro D1	Litoral Sur D3	NOA D6	Santa Fe C D9	Oeste Arenoso D7	Oeste D8	Santa Fe Sur D10	Este D2	MyS D4
(1) Average farm size (hectares)		228	327	343	134	514	299	804	262	296
(2) Land rental value (US\$/ha)		370	237	170	333	267	333	315	285	219
		Production Increase (US\$/ha)								
(3) Improvement only PMI (US\$/ha)	5.5%	108.8	87.6	96.5	109.5	117.3	111.8	106.9	121.3	107.4
(4) Improvement only LEI (US\$/ha)	3.7%	72.4	58.3	64.2	72.9	78.1	74.4	71.1	80.9	71.6
(5) Improvement both PMI and LEI (US\$/ha)	9.4%	185.3	149.2	164.3	186.5	199.7	190.3	181.9	202.2	178.9
(6) Ratio (5)/(2) %		50.1	62.9	96.7	56.0	74.8	57.1	57.8	70.9	81.7
(7) Total Impact (5)x2 (US\$ '000)		42.2	48.8	56.4	25.0	102.6	56.9	146.3	53.0	53.0

One possible explanation for this divergence is that the *PMI* and *LEI* indexes may be correlated with unmeasured “input quality”: farms with (say) high *PMI* may not only have high-quality production management, but a higher-than average (and unmeasured in the production function specification) quality labor, herd, pastures or milking equipment. If this is the case, divergence between managerial input marginal productivity and input prices will be overestimated, as improvement in the managerial input is accompanied by increased in (non-managerial) inputs used, increases that are not captured in the estimated production function.

Quality corrections are made on two of the included inputs: land and overhead expenses. In the case of land, the estimated rental rate was used to correct for different land qualities. Further, area-specific dummies capture additional land or location differentials. The use of monetary values for the overhead expense input should take care of quality differences in this set of inputs. Inputs herd size, supplementary feed and labor

are not quality-corrected, and if indeed quality of these is correlated with the managerial input indexes, biased estimation of marginal productivity of these will occur.

The issue of possible overestimation of the impact of improvement of managerial quality resulting from co-variation between managerial and (unobserved) non-managerial input quality certainly deserves additional attention. The question to be answered is what would the “correct” marginal productivities of *PMI* and *LEI* be if varying input quality would be taken into account not only for land and overhead expenses (as done here) but for labor, animal numbers and supplementary feed). Account has to be taken, however, of the possibility that higher managerial quality may in some cases result in increases in input quality not necessarily through the purchase of more expensive inputs but through “more bang for the buck”. For example, better selection of cows, or of feed inputs results in “higher quality inputs”. If this is the case complex issues arise as increased input quality is one of the outputs of improved managerial performance.

While overestimation of marginal productivity of the *PMI* and *LEI* inputs is certainly possible, it should also be pointed out that only the “worker effect” impact of managerial ability is analyzed here (more output from a given input vector). The literature on human capital and production efficiency (see e.g. Huffman, 2000) points out that *allocative* effects could be of more importance than the direct worker effects. These allocative effects relate to improved input-level and output combination decisions in the face of changing relative prices.

It should also be noted that the sum of elasticities of the “conventional” inputs in the OLS estimated production function (1.01) indicates constant returns to scale. However, if managerial ability (*PMI* and *LEI* indexes) increases proportionally the returns to scale parameter increases to 1.20. Higher-ability managers will thus be able to expand operations, while lower-ability managers will not find advantage in doing so. Welch, for example, points out to the complementarities existing between managerial ability and farm size (Welch, 1978).

Lastly, in the sample of farms analyzed here managerial quality is probably higher than that found in average farms of the country. If this is indeed the case, at the country-wide level the impact on production and economics results of improving different dimensions of managerial expertise should be even higher than than found here.

Final Comments

For the farms analyzed here, managerial ability appears to account for substantial differences in production efficiency. These differences could result in the gradual growth in size of “high managerial ability” farms, and the gradual retreat or even disappearance of farms where managerial ability is lower. Changes such as these are already occurring in Argentina and other countries. Findings also suggest that programs aimed at improving managerial performance could well have substantial payoffs.

In recent years considerable attention has been focused on the effectiveness of extension services and other types of services aimed at transferring know-how to agricultural producers. For example, Anderson and Feder (2003) report opportunities for information agricultural extension services, but also warn that in many (if not most) cases these services have had a relatively small impact on efficiency and farm profitability. Somewhat surprisingly, the literatures dealing with information-delivery systems (e.g. Anderson and Feder, 2003) and the one dealing with efficiency of production (e.g. Bravo-Ureta, 2002) have followed different paths. However; these two strands of research are clearly related: farm-level differences in efficiency are a result of limitations with which management is carried out. Extension services are one of the ways in which these limitations can be overcome.

Relaxing managerial constraints calls for improved understanding on how managers acquire and then use information. The approach used here of having farm advisors “grade” management in a given farm, and then analyzing the importance of these “grades” in accounting for differences in farm efficiency can be used to estimate the impacts of publicly or privately-sponsored aimed at improving farm-level performance. The impact of these services can be considered a two-step “production process”: the one analyzed here maps subjectively evaluated management performance with firm-level results. The other link refers to the impact of knowledge-transfer programs on subjectively-evaluated managerial decision-making and execution skills.

If this two-step production process is better understood, progress could be made on improved understanding of information-delivery and training projects aimed at agricultural producers.

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