Technical efficiency measurement: an application on dairy farms in Uruguay

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Abstract

G. Pérez-Quesada and F. García-Suárez. Technical efficiency measurement: an application on dairy farms in Uruguay. The productivity of Uruguayan dairy farms has been consistently growing for the last 40 years. This process has implied the adoption of new technologies, which have had significant effects on the production system. The efficiency with which available technologies are used influence output growth. Hence, assuring and enhancing dairy farms' productivity and efficiency represent an important challenge to improve the competitiveness of the sector and achieve sustained economic growth. The overall objective of this study is to analyze the efficiency performance of dairy farms in Uruguay. Using a cross-sectional database, this study estimates a Cobb-Douglas stochastic production frontier and technical inefficiency model for dairy farms to determine the effect of each input on the production frontier and the principal factors that explain differences in farm efficiency. According to the empirical results, the average technical efficiency for dairy farms is 74%, and the major determinants of efficiency differences are farmers' specialization in dairy farming and the usage of artificial insemination. Overall, farm profiles indicate that those in the high efficiency group achieve a higher level of milk production than those less efficient; and they produce under a more intensive production system than farmers in low efficiency groups.

Key words: cross-sectional data, stochastic production frontier, technical efficiency.

INTRODUCTION

Over the past four decades, the Uruguayan dairy sector has exhibited remarkable technological development. This process of technology adoption has implied significant changes in dairy farming's production system. The pastoral extensive model of production based on natural conditions has evolved into intensive farming based on cultivated pastures and a higher supply of better quality feed (Durán, 2004). Productivity gains are a result of a more intensified farming system, which has led to

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the sustained growth of both total milk production and milk sold to processing industries.

Globalization and the high competitiveness of milk production have driven dairy farmers not only to produce more milk but also to increase their efficiency and productivity to avoid being displaced from international markets. The strong international competition reveals the importance of improving productivity by adopting new technology and making the best use of current practices, as a mechanism to build competitiveness. Although dairy farming in Uruguay has a comparative advantage, meaning a lower cost of production compared to other countries, the whole sector must deal with important challenges to be competitive in the international dairy market (Chaddad, 2009). Therefore, milk production growth obtained by an increase in productivity seems to be the key to remaining competitive in international markets.

The most studied component of productivity is technical efficiency (TE) because it provides valuable information to policy formulation and farm decisions that are focused on the improvements of farm performance (Bravo-Ureta *et al*., 2008). Frontier production functions have been widely applied in the analysis of TE measurement among farmers in developed and developing countries. Battese (1992) presented a survey of empirical applications with estimates of frontier production functions to obtain a measurement of TE. Bravo-Ureta and Pinheiro (1993) reviewed the frontier production function literature dealing with farm level efficiency in developing countries. More recently, Bravo-Ureta *et al*. (2007) present a meta-regression analysis including farm level TE studies of developing and developed countries. Another relevant contribution to the existing literature was done by Moreira and Bravo-Ureta (2009). They also examined the impact of study-specific attributes on TE estimates, using a meta-regression analysis focused on dairy efficiency studies.

Although the dairy sector plays an important role in the Uruguayan economy, TE analysis has not been the focus of recent studies. There are two studies that have looked at Uruguayan dairy farm efficiency performance: Vaillant (1990) and Grau *et al*. (1995). On the other hand, Bravo-Ureta *et al*. (2008) applied stochastic production frontier analysis using unbalanced panel data sets for dairy farms from Argentina, Chile and Uruguay.

The focus of the present study is on the efficiency of Uruguayan dairy farms. The overall objective is to contribute to the understanding of dairy farming efficiency performance. Achieving a higher level of knowledge about the determinants of the farmer's TE allows us to better understand the relationship between the resources used in milk production and the obtained output. In this sense, we explain efficiency differences across farms and determine the potential for dairy farms to increase productivity under current production technology.

This study contributes to the dairy farming efficiency and productivity literature available in Uruguay because it uses a Stochastic Frontier Analysis (SFA) methodology for cross-sectional data for the first time. Moreover, we use a representative sample for empirical estimation, which is derived from a survey conducted by the National Institute of Milk (INALE) in 2014.

MATERIAL AND METHODS

Stochastic production frontier

To measuring efficiency, we implement the stochastic production frontier model independently developed by Aigner *et al*. (1977) and Meeusen and Van den Broeck (1977). It simultaneously accounts for statistical noise and technical inefficiency. Using cross-sectional data and a generalized production function the model can be represented as follows:

$$y_i = f(x_i, \beta)\ exp\{\varepsilon_i\} \qquad (1)$$

$$\varepsilon_i = v_i - u_i \qquad (2)$$

where y_i is the output of the firm i $(i = 1, 2, \ldots, n)$, x_i is a vector of inputs, β is a vector of unknown parameters, and ε_i is the "composed error" term. The error term is farm specific and is composed of two independent components.

The first element v_i is a symmetric error component that captures random shocks and statistical noise, which are outside farmer's control, such as weather, natural disasters, and measurement error. This term is assumed to be an independent and identically distributed normal random error with zero mean and constant variance $(v_i \sim N(0, \sigma_v^2))$.

The one-side, non-negative error term u_i captures technical inefficiency relative to the stochastic frontier, assumed to be independently distributed as positive truncated normal $u_i \sim N(\delta' z_i, \sigma_u^2)$. According to Kumbhakar *et al.* (1991), u_i is composed of a deterministic component, that is a function of some firm specific characteristics, and a random component:

$$u_i = \delta' z_i + w_i \qquad (4)$$

$$\varepsilon_i = v_i - (\delta' z_i + w_i) \qquad (5)$$

where z_i is a vector of explanatory variables that may influence firm efficiency performance, δ is the associated vector of parameters to be estimated and w_i is a random variable whose distribution is $N^+(0, \sigma_w^2)$. A detailed analysis of inefficiency error term distributional forms can be found in (Kumbhakar and Lovell, 2000).

Following an output-oriented measurement and given a stochastic production frontier, technical efficiency can be defined as:

$$TE_i = \frac{y_i}{y_i^*} = \frac{f(x_{ij}, \beta) exp\{v_i - u_i\}}{f(x_{ij}, \beta) exp\{v_i\}} = exp\{-u_i\} \ (6)$$

where y_i is the observed output, and y_i^* is the maximum output that can be produced given the inputs and technology available. The inequality $0 \leq TE_i \leq 1$ is also met due to $y_i \leq y_i^*$. Efficiency is a measure of comparing current performance with the best practice, and the best practice is defined by the production function.

Simultaneous estimation of parameters in the stochastic production frontier and in the technical inefficiency model $(\beta, \delta, \sigma_v^2, \sigma_u^2)$, can be obtained using ML method under the assumptions that v_i and u_i are distributed independently of each other and of the regressors. Battese and Corra (1977) found convenient to express the log-likelihood function in terms of the variance parameters: $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2 / \sigma^2$. The variance ratio γ reflects which part of the total deviation of the optimal product, given by the frontier, is attributed to technical inefficiency effects.

The estimation of farm specific level of technical efficiency is obtained using the decomposition proposed by Jondrow *et al.* (1982). The main idea is that the conditional distribution of the non-negative random variable u_i, given the random variable $\varepsilon_i = v_i - u_i$, is observable. Therefore, either the mean or the mode of the conditional distribution $(u_i|\varepsilon_i)$ could be used to estimate TE of each firm.

$$TE_i = \exp(-u_i) = \exp(-\delta' z_i - w_i) \ (7)$$

$$\widehat{TE_i} = \exp(-\hat{u}_i) \qquad (8)$$

where $\hat{u}_i$ can be the mean or the mode of the conditional distribution $(u_i|\varepsilon_i)$.

Data and empirical model

The data used in this study is a cross-sectional sample that was derived from a survey conducted by INALE in 2014. The sample has five strata which were defined considering annual milk production, including 276 dairy farms located in 8 departments of Uruguay[2]. The farms represent 90% of the total milk production and are highly specialized in dairy production. The usage of a representative sample is the main difference between this study and Bravo-Ureta *et al*. (2008) which use a sample that includes 70 dairy farms that do not represent the entire population. The collected data corresponds to the 2013/14 agricultural year. Table 1 depicts a summary of the data with the different variables, dependent and explanatory, which are included in our stochastic production frontier model.

Table 1: Descriptive statistics for variables used in the frontier (n=276)

Variable	Description	Mean	SD	Min	Max
y	Milk (L)[1]	1,676	1,672	26	9,579
x_1	Cow (n)	308	298	7	2,250
x_2	Labor (n)	8	6	1	30
x_3	Feed (kg)[1]	898	997	4	6,633
x_4	Pasture (ha)	226	237	5.6	1,456

Note: (1) In thousands

As we implement a parametric approach, a specific functional form for the production frontier is required. A likelihood ratio test was used to help confirm which functional form fits the data significantly better[3]. We test if a Translog function fits the data better than the Cobb-Douglas which is a more restricted form. Results show that it is not possible to reject the null hypothesis (H_0: $\beta_{ij} = 0$) that the nested functional form can be justified at a 5% significance level meaning that the Cobb-Douglas form is suitable specification for our data ($\lambda_{10} = 14.47, p > 0.05$). Thus, the empirical model in this study is based on the estimation of a Cobb-Douglas stochastic production function in which dependent and explanatory variables are expressed in natural logarithmic form:

$$lny_i = \beta_0 + \beta_1 lnx_{1i} + \beta_2 lnx_{2i} + \beta_3 lnx_{3i} + \beta_4 lnx_{4i} + v_i - u_i \qquad (9)$$

$$u_i = \delta_0 + \delta_1 z_{1i} + \delta_2 z_{2i} + \delta_3 z_{3i} + \delta_4 z_{4i} + \delta_5 z_{5i} + \delta_6 z_{6i} + w_i \qquad (10)$$

where the subscript i (i=1, 2,…,n) refers to the ith sample farm. The dependent variable (y_i) represents the total liters of milk produced during the year for each farmer i. Following the literature and the data available we include four explanatory variables: x_1 denotes the total number of milking cows, x_2 is the total number of employees including family and hired labor, x_3 is defined as the total consumption of feed including concentrated feed, hay and silage (kg), and x_4 is the pasture variable measured as the total area under cultivated forage (ha).

Technical efficiency is most frequently associated with the role of management in the production process, and it indicates the gain that can be achieved by simply improving

[2] Canelones, Colonia, Flores, Florida, Paysandú, Río Negro, San José and Soriano.

[3] The likelihood-ratio test statistic is calculated as: $\lambda = -2[\log(\text{likelihood } (H_0)) - \log(\text{likelihood } (H_1))]$, and it has a χ^2-distribution with parameter equal to the number of parameters assumed to be zero under the null hypothesis.

management (Farrell, 1957). Moreover, according to Coelli *et al*. (2005) exogenous variables that characterize the environment where the firm operates could have an influence on the ability of a manager to convert inputs into outputs. Hence, it is useful to distinguish between non-stochastic variables that are observable and could be controlled by the frim, and stochastic variables that are not under the firm's control such us the weather. However, unlike physical factors such as land, labor, or capital, management is not directly observable. This can complicate any analysis that tries to explain the impact of management on firm performance.

One possible solution to avoiding the former problem is to assume that management and environmental conditions are captured by the composed error term when a stochastic production frontier is estimated. Other studies introduce in the production function some variables in order to capture different environmental conditions. Mukherjee *et al*. (2013) used climatic indexes in production frontier to incorporate key climatic variables such as temperature and humidity. Moreover, Qi *et al*. (2015) introduce climatic variables into stochastic production frontier to measure the effects of climatic conditions on dairy farms productivity.

An alternative solution, implemented in this study, consists of explaining the asymmetric error term and expressing it as a function of certain variables that have an effect on TE. This is common in empirical studies that seek to quantify the influence of management on firm technical performance. The variation in TE is expressed as a function of management ability through the inclusion of socio-economic variables in the analysis.

In our study environmental conditions are considered as part of the stochastic error term since our dataset is a cross-sectional data and does not include any suitable variable to reflect environmental characteristics. On the other hand, we use six explanatory variables to define the inefficiency model, and to capture some farm specific management characteristics. The maximum level of education achieved by the primary decision-maker is measured as a categorical variable, where z_1 and z_2 are dummies equal 1 if the maximum level is secondary school or university, respectively.

As more than half of farmers do other productive activities as their second source of income, it is important to measure how specialized farmers are. To do this, variable z_3 is defined as the ratio of the total land (including land owned plus land leased) that is used exclusively for milk production to the total land available for any other production. Land used for milk production includes land devoted to milking cows, and heifers. We compare the performance of those farmers who use most of their land for milk production (z_3 close to one) and the performance of those who use part of their land to carry out other productive activities. Farmers who are specialized in milk production tend to concentrate all their resources and effort on this activity, which may allow them to increase their knowledge and experience.

To reflect other management strategies among the farmers we include the following three dummy variables. z_4 equals 1 if the farmer used artificial insemination to improve herd genetics. Although artificial insemination could be defined as an explanatory variable of milk production, we include it in the inefficiency model for the following reasons. Firstly, the database does not have data about artificial insemination's costs to define a quantitative variable. Secondly, artificial insemination requires some degree of precision to be implemented. Also, the farmer needs to have some specific knowledge about this technique to be able to apply it successfully. In these sense, artificial

insemination might be thought of as a proxy for farmer's management abilities.
Finally, farmers who receive professional assistance could improve their efficiency because they can make better decisions about the productive process and its organization. Therefore, two variables are defined: z_5 equals 1 if the farmer paid for veterinary or agronomic assistance, and z_6 equals 1 if the farmer paid for accounting assistance.

RESULTS AND DISCUSSION

Table 2 presents parameter estimates for the estimated stochastic production frontier model. All the estimations were done using Frontier for R that uses the Fortran code of FRONTIER 4.1 package, which provides the maximum likelihood estimates for the parameters of stochastic frontier (Coelli, 1996).

Table 2: Stochastic production frontier estimates

Variable	Coefficient	SD
Frontier		
Constant	6.988***	0.250
Cow	0.570***	0.047
Labor	0.071*	0.039
Feed	0.271***	0.027
Pasture	0.075**	0.031
Inefficiency Model		
Constant	1.093***	0.175
Secondary	-0.020	0.067
University	-0.083	0.103
Specialization	-0.542***	0.186
Insemination	-0.342***	0.089
Vet or agronomic assistance	-0.226***	0.073
Accounting assistance	-0.221***	0.079
σ^2	0.076***	0.018
γ	0.789***	0.082
Log-likelihood	61.65	
Mean TE	0.810	

Note: *, ** and ***, denote statistical significance level at 10%, 5%, 1% respectively.

The estimate for parameter γ is equal to 0.789, which lets us conclude that both statistical noise and inefficiency are important for explaining deviations from the production function. However, inefficiency is more important than noise, which means that part of the difference between observed and maximum frontier output can be explained by the difference in a farmer's level of TE by adopting different management practices. Besides, it is possible to test the relevance of inefficiency component using a likelihood ratio test. Under the null hypothesis ($H_0 = \gamma = \delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = \delta_7 = 0$) the test statistic follows a mixed χ^2-distribution (Coelli, 1995)), and critical values can be obtained from Kodde and Palm (1986). The null hypothesis is strongly rejected by the data ($\lambda_8 = 76.45, p < 0.05$). This result implies that either statistical noise and inefficiency are important for explaining deviations from the production frontier.

Therefore, stochastic frontier model better fits the data compared to OLS model.

As Table 2 shows, all production function coefficients are non-negative meaning that the function satisfies the monotonicity property. It implies that additional units of an input will not decrease output. The sum over the coefficients of all inputs is very close to one, indicating that technology might present constant returns to scale (CRS). To confirm this result, we used a likelihood ratio test. The null hypothesis that the production frontier present constant returns to scale ($H_0: \beta_1 + \beta_2 + \beta_3 + \beta_4 = 1$) was not rejected at a 5% significance level ($\lambda_1 = 0.47, p > 0.05$). CRS implies that increasing all variables inputs by 1% will lead to an increase in output levels of 1%. There was no evidence for economies scale. Therefore, improvements in technology and efficiency could be more significant in explaining productivity change than farm size. However, Bravo-Ureta *et al*. (2008) found increasing returns to scale in their study on technological change and TE for dairy farms in Uruguay which means that the farms in the sample operate at a sub-optimal size.

In the Cobb-Douglas function, the output elasticities of the inputs are equal to the corresponding coefficient if all inputs are measured in logarithmic form. As we can see in Table 2, all output elasticities are positive and statistically significant. These results reveal that the variables milking cows, labor, feed and pasture positively influence milk production. This implies that a 1% increase in any of the independent variables, i.e. the herd size, the number of workers, the feed consumption and the area under cultivated forage, results in an estimated increase in milk production of 0.570, 0.071, 0.271 and 0.075%, respectively.

Of all input variables, the number of milking cows have the highest effect on milk production level. This result is consistent with other studies which use cross-sectional or panel dataset, including Kumbhakar *et al*. (1991), Heshmati and Kumbhakar (1994), Cuesta (2000), Kompas and Che (2006), Cabrera *et al*. (2010), Bravo-Ureta *et al*. (2008), Al-Sharafat (2013) and Qi *et al*. (2015). Regarding the labor variable, it is important to note that it is significant at a 10% significant level, and Bravo-Ureta *et al*. (2008) found that this variable is not significant in explaining milk production.

In terms of the technical inefficiency model, a negative sign on a coefficient indicates that an increase in the value of that variable results decreases inefficiency and a positive value increases inefficiency. The empirical results show that all the explanatory variables that were included, except for the dummies that reflect educational level, have a significant negative impact on technical inefficiency. The non-significance of educational level might arise from measurement problems since schooling years were not available in the data. Holding everything else constant, those farmers who are more specialized in milk production, and those who use artificial insemination, veterinary, agronomic or accounting assistance, achieved better performance that is associated with a lower technical inefficiency level, compared to farmers who have other productive activity, or do not use artificial insemination or receive professional assistance. However, the major determinants of efficiency differences are the level of specialization in milk production and the use of artificial insemination.

The mean TE in the sample is 0.81 indicating that on average farmers reached 81% of their technical abilities and the remaining percentage were not realized (Table 2). Even though Bravo-Ureta *et al*. (2008) used unbalanced panel data to estimate stochastic production frontiers, they found that the mean TE of dairy farms in Uruguay was 0.81 and its maximum level was 0.97. Also, the average level of TE that we obtained is comparable to the average TE that Bravo-Ureta *et al*. (2007) presented in their meta-regression analysis of TE in agriculture. For the TE studies that consider countries from Latin America and implement a stochastic frontier analyze, the authors found an average TE level equal to 0.78.

As the sample represents the total dairy farm population, it is possible to analyze the empirical results for the entire sector. Hence, when we expand the sample's results to the population we obtain that the mean TE of dairy farms in Uruguay is 0.74. This suggests that farmers are not fully technically efficient. Farmers could increase milk production using the current level of inputs and production technology available. They can improve their productivity and efficiency if they implement more efficient farm practices. The lower mean TE of dairy farms obtained when we consider the population shows the higher weight that smaller farmers have in the sample. This represents the reality of dairy farms in Uruguay where most of them are small or medium farmers.

Efficiency has a direct effect on the output quantity. Therefore, it is expected that the efficiency estimates are highly correlated with the output. A positive and significant correlation (0.64) was found between TE and milk production, meaning that the higher the milk production the more efficient the farmer is. On the other hand, the association between TE and total land that is used for dairy farming is significant but weaker (0.35). These results are consistent with the results presented by Grau *et al*. (1995) and Vaillant (1990). The correlation is also weak (0.41) if we consider the relationship between farm size, measured as herd size, and efficiency. These findings reflect that the association between TE and farm size, measured as the total land used for dairy farming or the herd size, is not clear. Moreira *et al*. (2012) found that farm size was not associated with productivity growth in dairy production in Chile. Although TE is also positively associated with labor, feed consumption and pasture, correlations are relatively weak (0.30, 0.48 and 0.38).

The distribution of TE scores for dairy farms is presented in Table 3. As the table indicates, 35.5% of the farms present a level of TE below 0.70, while almost 50% of them achieve a level of TE between 0.70 and 0.89. Only 16.3% are in the higher group where the mean TE is 0.92.

Table 3: Distribution of the farm level measures of technical efficiency (TE)

TE	Farms (n)	Mean TE	Farms in TE groups (%)
<0.5	265	0.44	9.6
0.5-0.59	282	0.56	10.2
0.6-0.69	407	0.63	14.7
0.7-0.79	582	0.74	21.0
0.8-0.89	780	0.85	28.2
>0.9	450	0.92	16.3
Total	2,766	0.74	100

Using the farm level efficiency measures from the frontier estimates, we can obtain a profile of dairy farms by efficiency ranking, which are divided into five groups as Table 4 shows. The Bonferroni test was used to analyze differences in average values of each variable between efficiency groups.

Table 4: Average value of milk production and explanatory variables by efficiency groups[1]

TE farm group	Farms (n)	Milk (l)[2]	Cows (n)	Labor (n)	Feed (kg)[2]	Pasture (ha)	Land (ha)[3]
0.88-1	601	1,261[a]	199[a]	5.65[a]	575[a]	138[a]	258[a]
0.81-0.87	544	876[ab]	170[ab]	5.11[a]	454[a]	117[ab]	227[ab]
0.72-0.80	527	625[bc]	137[abc]	4.83[ab]	357[ab]	100[abc]	208[abc]
0.60-0.71	547	321[c]	91[bc]	3.21[b]	165[b]	71[bc]	129[bc]
0-0.59	547	174[c]	62[c]	2.99[b]	98[b]	41[c]	91[c]

Note: (1) Values sharing the same letter between groups are not significantly different at a 5% significance level. (2) In Thousands; (3) Land used exclusively for milk production.

Milk production is on average statistically and significantly different between low and high efficiency groups. The most efficient farmers achieve a higher level of milk production than those less efficient. This result confirms the positive correlation between efficiency and milk production.

Herd sizes is statistically different comparing high and low efficiency groups, indicating that larger farms, in terms of milking cows, achieve a higher efficiency level than smaller ones. Nevertheless, the difference is not significant considering medium efficiency groups. When we measure farm size in terms of the land available for milk production, we observe that the most efficient farmers are larger than the least efficient. However, the differences in average values of milking cows and land among efficiency groups are not very large in magnitude among groups with a higher efficiency level. These results confirm the weak correlation presented above between TE and farm size (in terms of milking cows or land).

Finally, labor, feed and pasture are also statistically different when we compare high and low efficiency groups (Table 4). These results indicate that farms in the high efficiency group are larger in terms of the used labor, feed consumption and area under cultivated forage than those in the lower efficiency group. Similar results are presented in Kompas and Che (2006) which compared the average value of farm characteristics by efficiency groups.

As can be seen in Table 5, there is no doubt about the association between milking cow productivity and efficiency. It is statistically different across all the TE farm groups indicating that the most efficient farmers combine resources in a better way than those least efficient to achieve a higher level of production per milking cow. The milk yield per cow in the high efficiency group is more than twice than that of low efficiency group. On the other hand, milk production per hectare of land that is used exclusively for milk production is also significantly different if we compare the least and the most efficient farms. Furthermore, the number of milking cows per hectare in the high efficiency group is significantly different and higher than in the low efficiency group.

The proportion of pasture to total land used for milk production is not statistically and significantly different among efficiency groups. This result is consistent with Grau *et al.* (1995) that found a non-statistically significant correlation between TE and the percentage of pasture for CREA farmers.

Table 5: Average value of farm characteristics by efficiency groups

TE farm group	Liters/ cow[1]	Liters/ Ha[1]	Feed/l	Concen/l	Forage/l	Labor/Ha	Cow/Ha	Ratio of pasture
0.88-1	6.35[a]	5.48[a]	0.40[a]	0.21[ab]	0.19[a]	0.03[a]	0.86[b]	0.53[a]
0.81-0.87	5.29[b]	4.40[b]	0.46[ab]	0.21[ab]	0.25[ab]	0.03[a]	0.83[ab]	0.52[a]
0.72-0.80	4.71[c]	3.23[c]	0.46[ab]	0.21[ab]	0.25[ab]	0.04[ab]	0.70[a]	0.47[a]
0.60-0.71	3.47[d]	2.67[c]	0.43[a]	0.18[a]	0.24[ab]	0.03[a]	0.77[ab]	0.52[a]
0-0.59	2.75[e]	2.00[d]	0.53[b]	0.25[b]	0.27[b]	0.04[b]	0.73[a]	0.46[a]

Note: (1) In thousands

Comparing the average amount of feed used to produce a liter of milk, we can observe that it is statistically different between the most efficient farmers and the least efficient. The most efficient farmers use less concentrated feed and forage to produce a liter of milk than those less efficient. However, when we divide feed consumption into concentrated feed and forage, we find that only the consumption of forage per liter of milk is statistically different between farmers in the high efficiency group and those in the low efficiency group. This reflects that in grazing systems there is an efficiency gain of grazing instead of harvesting and feeding forage in a semi-stabled area. In Uruguay, all farms use grass-production as feed for cows and given the measure of concentrated and forage we can infer the amount of grass-production needed to produce milk. As a result, the most efficient farms are those that produce more grass for grazing.

Considering the differences in magnitude of the average value of feed per liter, they are not very large among the efficiency groups. Therefore, the outstanding difference in productivity per milking cow between efficiency groups might be not a direct consequence of the usage of feed. It seems that the consumption of concentrated feed and forage should be complemented with a higher consumption of grass or better herd genetics to obtain productivity improvements.

On the other hand, the consumption of feed per milking cow is higher for the most efficient farms and the average value is significantly different between TE farm groups (Table 6). Kompas and Che (2006) also found that concentrated feed per cow was largest for the high efficiency group. The higher supply of concentrated feed allows for an increase in the number of cows per hectare of land. This is an important feature of intensive dairy farming. The mentioned higher supply of feed was a fundamental change that occurred during the technological advance of the dairy production system in Uruguay. Still high grass production is the key to sustain higher carrying capacity of the system meaning that intensification starts improving grass-production.

From this analysis among efficiency groups arises the fact that the production system of the most efficient farms tends to be that of intensive dairy farming. Cabrera *et al.* (2010) found that an increase in the intensification system of a farm would implies higher technical efficiency levels. Considering the most and the least efficient farms, the empirical results show that the former achieve productivity levels that are more than twice the productivity level of less efficient farms. Furthermore, the number of dairy cows per hectare of land is 17.8% higher on the most efficient farms than for the less efficient.

Table 6: Average value of feed per milking cow (kg/cow) [1]

TE farm group	Feed/cow	Concen/cow	forage/cow
0.88-1	2.64[a]	1.39[a]	1.25[a]
0.81-0.87	2.53[a]	1.13[ab]	1.40[a]
0.72-0.80	2.23[a]	1.02[b]	1.21[ab]
0.60-0.71	1.56[b]	0.66[c]	0.91[bc]
0-0.59	1.51[b]	0.73[c]	0.78[c]

Note: (1) In thousands

As this study shows, there exists an intensification process in dairy farming in Uruguay. The smallest farms are the ones facing more difficulties in obtaining better performance. However, they could increase milk production if they improve efficiency. This means that the ability of a farmer to obtain the maximum output with the current quantities of inputs and technology available, can be improved. Therefore, productivity gains for the smallest farms due to improvements of TE seems to be more relevant than for the largest farms who already present higher TE levels.
From a policymaking point of view, it seems important to make policies focused on improving the ability of farms to use new techniques and combine inputs. Policies, which attempt to promote the adoption of new technologies, should be accompanied by policies oriented to improving managerial practice, learning by doing and spreading new technological knowledge. The information that farms use to make their decisions is different among farms, and that impacts TE.

CONCLUSION

Empirical results showed that all input variables were statistically significant with a positive effect on milk production. The highest effect on production was the number of milking cows followed by feed, pasture and labor. The average level of TE in the whole sector was 74%, which suggests that dairy farmers in Uruguay can expand milk production by 26% using the current level of inputs and production technology available. They can improve their productivity and efficiency implementing more efficient farm practices. The principal determinants of TE differences were the level of specialization in milk production and the artificial insemination. Therefore, farmers who focus on dairy farming or use artificial insemination can achieve higher levels of efficiency than those who have less experience or are not using artificial insemination. Also, veterinary, agronomic and accounting assistance have a significant negative impact on technical inefficiency. Finally, empirical results show that farmers in the high efficiency group follow a more intensive production system than farmers in the low efficiency group.

RESUMEN

El objetivo de este estudio es estimar y analizar la eficiencia técnica con la que operan los productores de leche en Uruguay. Utilizando una base de datos correspondiente al ejercicio agrícola 2013/14, derivados de una encuesta realizada por el INALE a productores de leche, se implementó la metodología de fronteras estocásticas de producción para determinar los principales insumos que afectan la producción de leche y los principales factores que explican diferencias en el nivel de eficiencia técnica entre los productores. De acuerdo con los resultados obtenidos, el nivel de eficiencia técnica promedio para los productores de leche es de 74% y los principales determinantes de la misma son el nivel de especialización en la producción de leche y el uso de inseminación artificial. Esto significa que aquellos productores más especializados en la producción de leche y aquellos que usan inseminación artificial, operan con una eficiencia técnica mayor comparados con aquellos que combinan la lechería con otras actividades económicas o que no inseminan artificialmente su ganado. Analizando el perfil de los productores de leche ordenados según su nivel de eficiencia, puede observarse que los productores con mayor nivel de eficiencia técnica producen bajo sistemas de producción más intensivos que aquellos productores con menores niveles de eficiencia.

Palabras claves: datos de corte transversal, frontera estocástica de producción, eficiencia técnica.

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