TECHNICAL EFFICIENCY OF DAIRY FARMS IN URUGUAY: A STOCHASTIC PRODUCTION FRONTIER ANALYSIS.

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ABSTRACT

The dairy sector is one of the most influential sectors and plays an important role in the economic and social structure of Uruguay. Assuring and enhancing the dairy sector productivity and efficiency represent an important challenge in order to improve the competitiveness of the sector and achieve a sustained economic growth. Consequently, the overall objective of this study is to analyze the efficiency performance of dairy farms in Uruguay. Using a cross-sectional database this paper estimates a Cobb-Douglas stochastic production frontier and technical inefficiency model for dairy farms to determine the effect of each input in the production frontier and the principal factors that explain differences on farm efficiency. Results shows that highest effect on production is the number of milking cows followed by the total consumption of feed including concentrated feed, hay and ensilage. Although, veterinary, agronomic or accounting assistance matter, the major determinant of efficiency differences is the 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 are larger in terms of the herd size, used labor, feed consumption and area under cultivated forage than those in lower efficiency group.

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

INTRODUCTION

The dairy sector is one of the most important and influential sector in Uruguay. It plays an important role in the economic structure due to the aggregated high value it generates. Milk production represented 12.4% of the total agricultural production, and dairy product exports reached 9.7% of the total agro industrial exports in 2014[1]. The domestic consumption is covered and Uruguay exports about 70% of the total production. The total number of dairy farms who are specialized in milk production is 4341, who occupy a total area of 794 thousands of hectares. The percentage of farms that remit milk production to industries is 67%, and the total remitted milk was 2,014 millions of liters. Thus, the productivity of dairy farms achieved a level of 688 thousands of liters[2].

The Food and Agriculture Organization (FAO) warns that the world food economy is being increasingly driven by the shift of diets towards livestock products including milk, which is expected to increase particularly in developing countries. As a consequence, there could exist a higher demand for milk, which might be satisfied by an increase in milk production. It is expected that this milk production growth will occur principally in developing countries where most of production growth is derived from an increase in dairy herd. Nevertheless, the growth of herd is limited by the amount of water and land available. In order to increase productivity, these countries are forced to incorporate new technologies. On the other hand, the international dairy market is the most protected and subsidized worldwide, and it is dominated by a few exporter countries. Although the dairy sector in Uruguay has a comparative advantage, meaning a lower cost of production compared to other countries, it has to deal with important challenges to be competitive in the international dairy market. In this context, milk production growth as a consequence of increase in productivity seems to be the key to remain competitive.

[1] OPYPA Yearbook 2015. Ministry of Livestock, Agriculture and Fisheries of Uruguay.
[2]Agricultural Statistical Yearbook 2015. Ministry of Livestock, Agriculture and Fisheries of Uruguay.

Historically, dairy farms in Uruguay have based their competitiveness on natural conditions, which means that they have had a comparative advantage as a consequence of pastoral systems. However, this pattern has suffered important changes due to increased milk production leading to a stronger dependence on international markets. Given this, there is a need to continually build competitiveness within the dairy sector to remaining as a competitive player in international markets. Fortunately, over the last few years, there has been a continuous expansion of milk production in Uruguay. This can be explained as a result of a sustained increase in the process of technology adoption instead of increasing the available land for dairy farms. Studying farms efficiency and the potential sources of inefficiency are important factors from a practical and a policy point of view. Consequently, the overall objective of this study is to contribute to the understanding of Uruguayan dairy farming efficiency performance. Achieving a higher level of knowledge about the determinants of the farmer’s technical efficiency allows us to better understand the relationship between resources used in milk production and the obtained output. In this sense, we try to explain efficiency differences across farms and to determine the potential for dairy farms to increase productivity under current production technology.

Previous literature on this topic has focused on estimating the level of technical efficiency (TE) among samples of dairy farms. Two principal approaches have been developed for efficiency measurement: mathematical programming (nonparametric), commonly known as Data Envelopment Analysis (DEA); and econometric model (parametric) such as Stochastic Frontier Analysis (SFA). Both methods estimate the production frontier, which represent the best practice for a specific sample of farmers. According to Coelli et. al (1996), SFA has been the most adopted methodology in measuring farm efficiency performance in studies related to the agricultural sector because of its capacity to deal with stochastic noise.

We implement a SFA model to estimate the determinants of TE among dairy farms. The data used for empirical estimation is a cross-sectional database that is derived from a survey conducted by the National Institute of Milk (INALE) in 2014. The sample includes 273 dairy farms located in 8 departments of Uruguay. They represent 90% of the total production of milk and are highly specialized with most of their output coming from dairy. The collected data correspond to the 2013/14 agricultural year. This study contributes to the dairy farming efficiency and productivity literature available in Uruguay because it uses SFA methodology for cross-sectional data for the first time.

LITERATURE REVIEW

The measurement of TE among dairy farmers has been widely studied in developed countries. Although dairy sector has an important role in the Uruguayan economy, the TE analysis has not been the focus of the studies.

There are two studies that have investigated Uruguayan dairy farm efficiency performance: Vaillant (1990) and Grau et al. (1995). Both estimate a deterministic production function. In the first study, the author tries to identify opportunities and limitations of increasing milk production based on improving dairy farmer’s productivity. Vaillant (1990) estimates a production function using a cross sectional sample including 331 Uruguayan dairy farms for 1987. According to the results, the larger farms present higher levels of efficiency compared with smaller farms. It was found variability among the technologic practice as a result of a previous period characterized for an important technological change.

Grau et al. (1995) estimate a production function considering different size of farmers, using a panel data set which includes information about 537 farmers which integrate CREA[3] group. They found a high level of TE (90.13%) among farms concluding that concluding that there is little scope to productivity gains by improving the use of inputs and available technology. It seems necessary a shift in technologic frontier that allows higher levels of production. However, TE is heterogeneous when farmers are individually considered. Besides, the authors found a positive and significant association between efficiency and milk production, which implies that farms with higher levels of milk production are more efficient. It was also found a positive correlation between efficiency and grain feed use.

Bravo-Ureta et al. (2008) applied stochastic production frontier analysis, using unbalanced panel data sets for dairy farms from Argentina, Chile and Uruguay. Three SFA models were estimated, one for each country, using a Translog specification. In each case, the same four explanatory variables were used to explain the dependent variable, defined as annual output per farm: average number of cows; labor, measured in equivalent workers; purchased feed and veterinary inputs costs. The frontiers were used to evaluate economies of scale, rate of technological change, and TE. As a result, authors found that TE present mean values of 87%, 84.9% and 81.1% for Argentina, Chile and Uruguay, respectively. This result means that farmers of the three countries could increase their milk production while maintaining the usage level of inputs. It seems important to note some difference between this study and ours. First, we use an updated data to try to capture the increasing technology change. In addition, the sample used in the present study represents 90% of the total milk production in Uruguay.

Cabrera et al. (2010) and Wang (2001) are two relevant studies in the sense that they estimate TE using a stochastic production frontier based on a cross-sectional sample of dairy farms. Cabrera et al. (2010) analyze the effect of practices commonly used by dairy farmers and the effect of intensification on the performance of the farms. A sample of 273 farmers of Wisconsin is used to estimate the stochastic frontier and the technical inefficiency model. The empirical results showed that the average level of TE in the sample was 88%, indicating that farmers could expand milk production using the inputs and technology available. The variable with the highest effect on production is the number of cows followed by the total expenditure in crops, feeding, livestock, and labor. A proportional relationship between the size of the farm and the level of TE was not found, which suggests that improvements in technology and efficiency explain the level of productivity, not the size of the farm.

Wang (2001) estimates mean technical efficiency and technical efficiency of individual farms based on three distributional assumptions of the efficiency disturbance terms: half-normal, generalized truncated normal and normal one-parameter exponential. The stochastic production function is estimated using a cross-sectional sample of Pennsylvania dairy farms. Cobb-Douglas functional form is used in the model. The mean TE among the farmers reaches 85%. Considering the individual farm TE, the results indicate that large farms are technically more efficient than small farms.

MATERIALS AND METHODS

The frontier function methodology was first introduced by Farrell (1957) in order to measure efficiency comparing current performance with the best practice. His model known as a deterministic non-parametric frontier attributes any deviation from the frontier to inefficiency and does not define any functional form on the data. Several extensions of deterministic model presented by Farrell have been made in order to refine the frontier function methodology.

[3] Regional Agricultural Experimentation centers.

A more recent approach for measuring efficiency is the stochastic production frontier model that simultaneously accounts for statistical noise and technical inefficiency. It was independently developed by Aigner et al. (1977) and Meeusen et al. (1977) and it resolves the most serious deficiency of deterministic frontier approach: all deviation from the frontier are a consequence of inefficiency. Using cross-sectional data and a generalized production function the model can be represented as follows:

$$y_i = f\left(x_{ij}, \beta\right) exp\{\varepsilon_i\}$$

$$\varepsilon_i = v_i - u_i$$

Where y represents output, x is a vector of inputs, β is a vector of unknown parameters, and ε is the error term. The subscripts i and j denote the farm and inputs, respectively. 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 variable with zero mean and constant variance ($v_i \sim N(0, \sigma_v^2)$).

The one-side, non-negative error term $u_i \geq 0$ captures technical inefficiency (TI) relative to the stochastic frontier. If a farmer is technically efficient ($u_i = 0$), then he operates on its stochastic frontier, $f\left(x_{ij}, \beta\right) exp\{v_i\}$; if a farmer is technically inefficient ($u_i \geq 0$) then he operates beneath its stochastic frontier. The stochastic frontier defines the farmer's maximum feasible output given inputs and available technology in the presence of random shocks. The principal idea of SFA is that the distance from the observed output to the frontier output is partly due to inefficient production, and partly due to the random shocks experienced by the farmer. It is possible for a farmer to operate above the deterministic production frontier when the noise effect is positive and larger than the inefficiency effect.

Much of SFA is directed towards the prediction of the inefficiency effect. The most common output oriented measurement of TE can be defined as the ratio of the observed output (y_i) and the maximum feasible output (y_i^*) given the levels of inputs used by the farmer, (Coelli et al., 2005):

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

Because $y_i \leq y_i^*$, this measurement of TE takes values between zero and one. $TE_i = 1$ if the farmer is technically efficient, which means that he is producing the maximum feasible output level given the input quantities.

To estimate the SFA models, that is, to determine the unknown parameters ($\beta, \sigma_v^2, \sigma_u^2$), we must know the density of the composed error term (ε). To do so, explicit assumptions on the distribution of the inefficiency error term u_i need to be imposed. Meeusen et al. (1977) assumed an exponential distribution of u_i, Battese et al. (1977) assigned a half normal distribution, while Aigner et al. (1977) considered both distributions of u_i. More flexible distributional assumptions of u_i were considered by Greene (1980), who assumed gamma distribution, and Stevenson (1980) gamma and truncated normal distribution. The choice of inefficiency error term distribution is sometimes a matter of computational convenience (Coelli et al., 2005). In this study, FRONTIER 4.1 package[4] is used to estimates the parameters under the assumption that the u_i follows a half-normal or truncated-normal distributions.

Under the assumptions that v_i and u_i are distributed independently of each other and of the regressors, the parameters of the SFA can be estimated using the maximum likelihood (ML) method. Because ML estimators have many desirable large sample properties, they are preferred to other estimators such as corrected ordinary least squares (Coelli et al., 2005). Following Battese et al. (1977), the likelihood function can be expressed in terms of the variance parameters: $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2/\sigma^2$. Hence, the parameter γ, which takes values between zero and one, represents the importance of the inefficiency term. It is irrelevant if γ is equal to zero. In this case the results should be equal to Ordinary Least Square (OLS) results that implies $\gamma = 0$. On the other hand, if γ is one, the noise term is irrelevant and all deviations from the production frontier are explained by technical inefficiency.

Besides the mean TE, it is desirable to be able to estimate the farm specific technical inefficiency (u_i,). However, the prediction of the technical efficiencies of individual farms associated with the stochastic frontier production function was impossible until the study of Jondrow et al. (1982). The principal idea presented was that the conditional distribution of the non-negative random variable u_i, given that the random variable $\varepsilon_i = v_i - u_i$, was observable. Jondrow et al. (1982) proposed that either the mean or the mode of the conditional distribution $(u_i|\varepsilon_i)$ could be used. The mean is more commonly used than the mode, though, the mode has a more attractive interpretation as ML estimator (Kumbhakar et al., 2000). If the inefficiency error term follows a half-normal distribution $u_i \sim iid\ N^+(0, \sigma_u^2)$, mean is defined as following:

$$\widehat{u_\iota} = E(u_i|\varepsilon_i) = \sigma_* \left[\frac{f(\varepsilon\lambda/\sigma)}{1 - F(\varepsilon\lambda/\sigma)} - \left(\frac{\varepsilon\lambda}{\sigma}\right)\right]$$

Where $f(.)$ represents the standard normal density and $F(.)$ the standard normal cumulative density functions, $\sigma^2 = \sigma_u^2 + \sigma_v^2$, $u_* = -\sigma_u^2\varepsilon/\sigma^2$, $\sigma_*^2 = \sigma_u^2\sigma_v^2/\sigma^2$. We can also note that $-\mu_*/\sigma_* = \varepsilon\lambda/\sigma$ with $\lambda = \sigma_u/\sigma_v$.

After we have the estimations for u_i, technical efficiency measure for each farm is equal to:

$$\widehat{TE_\iota} = \exp(-\hat{u}_i)$$

Kumbhakar et al. (1991) extended this framework in which determinants of TI are explicitly introduced in the model. They assume that TI is composed of a deterministic component, that is a function of some farm specific characteristics, and a random component. The mean of TI is no longer invariant across observations. It is considered a function of exogenous variables specific of each farm. Thus, TI can be expressed as:

$$u_i = \delta z_i + w_i$$

where z_i is a vector of explanatory variables that may influence on-farm efficiency performance, δ is the associated vector of parameters to be estimated and w_i is a random variable whose distribution is $N^+(0, \sigma_u^2)$. Consequently, the inefficiency effects in the frontier model have positive truncated normal distributions that vary with z_i:

$$u_i \sim N(\delta z_i, \sigma_u^2)$$

[4] Tim Coelli and Arne Henningsen (2013). Frontier: Stochastic Frontier Analysis. R package version 1.0. http://CRAN.R-Project.org/package=frontier.

Assumptions about terms error (v_i and u_i) distribution, result in a left-skewed distribution of the total error term $\varepsilon_i = v_i - u_i$. Thus, it is rare that a farm has a large positive residual but is more likely that a firm has a large negative residual (Henningsen, 2014).

Simultaneous estimation of parameters in the stochastic production frontier (β) and in the technical inefficiency model (δ), 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. All these calculations are done using the FRONTIER package.

DATA AND EMPIRICAL MODEL

The data used in this study is a cross-sectional sample that is derived from a survey conducted by INALE in 2014. The sample includes 273 dairy farms located in 8 departments of Uruguay. They represent 90% of the total production of milk and are highly specialized with most of their output coming from dairy. The collected data corresponds to the 2013/14 agricultural year. Table 1 depicts some summary statistics of the Uruguayan dairy farms:

Table 1: Descriptive statistics for dairy farms (n=273)

Variable	Description	Mean	SD	Min	Max
y	Milk (lt)	1,660,039	1,617,944	26,300	9,578,899
x_1	Land (%)	82.2	19.3	19.6	100
x_2	Cow (n)	306	291	7	2,250
x_3	Labor (n)	8	6	1	27
x_4	Feed (kg)	887,822	964,137	4,456	6,633,208
x_5	Pasture (ha)	224	230	6	1,456

It is important to indicate that TE measurements are sensitive to the choice of functional specification (Giannakas et al., 2003). In this sense, the choice of an appropriate functional form affects the identification of the factors that determine individual performance. A likelihood ratio test[5] was used to help confirm which functional form fits the data significantly better. The null hypothesis is that all Translog coefficients are zero. Results led to the rejection of the Translog form in favor of Cobb-Douglas. 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:

$$lny_i = \beta_0 + \beta_1 lnx_{1i} + \beta_2 lnx_{2i} + \beta_3 lnx_{3i} + \beta_4 lnx_{4i} + \beta_5 lnx_{5i} + v_i - u_i$$

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 five explanatory variables: x_1 is defined as the percentage of the total land[6] that is used exclusively for milk production; x_2 denotes milking cows; x_3 is the total number of employees including family and hired labor; x_4 is defined as the total consumption of feed including concentrated feed, hay and ensilage (kg); x_5 is the pasture variable measured as the total area under cultivated forage (ha).

[5] It follows a χ^2-distribution under the null hypothesis
[6] Including land owned plus land leased

Three dummy variables were included in the inefficiency model: z_1 equals 1 if farmer used artificial insemination; z_2 equals 1 if farmer paid for veterinary or agronomic assistance; z_3 equals 1 if farmer paid for accounting assistance.

$$u_i = \delta_0 + \delta_1 z_{1i} + \delta_2 z_{2i} + \delta_3 z_{3i} + w_i$$

PROFILE OF DAIRY FARMERS

In this section we describe the most relevant characteristics of dairy farms that are being considered in this study. The sample includes 273 dairy farms located in 8 departments of Uruguay. They represent 90% of the total production of milk. However, the survey was not focused in the measurement of socio-economic aspects giving as a result that the sample is not representative of the socio-economic characteristics of the whole dairy sector in Uruguay. Because of that, this profile is not always expandable to the entire sector.

Considering farm size, measured as the total land available for production, 53% of the farmers have more than 50ha but less than 500ha. Only 7% are small while 40% of them are large with 500 or more hectare. The mean of total area for production reach 589ha. On the other hand, the average number of milking cows is 306 and around 60% of farmers have a number of milking cows which vary between 100 and 500.

In Table 2, the total number of farms is divided into three groups according to the total land available for production -small, medium and large. Farms with more than 500ha, produced on average 3,009,355lt during the 2013/14 agricultural year. However, if we consider milk production per hectare of land that is exclusively used for milk production, the land productivity is higher in small and medium farms with 3,932 lt/ha and 4,233 lt/ha respectively, than in larger farms that is 3,776 lt/ha.

Among all farms the principal productive activity is milk production. Nevertheless, 57% of them have a secondary productive activity. The two activities more frequently practiced together with milk production are livestock and cereal crops, representing 54% and 22% respectively of the farms that have a secondary activity. In the case of larger farms, 67% have other productive activity as a second source of income. Farms with less than 50 ha are more specialized than larger; the 44% of them have a secondary activity. The intensity ratio defined as the number of cows per hectare also shows that smaller farms are more specialized in milk production.

Table 2: Average values of variables by farm size group

Farm group (Ha)	Farms (n)	Milk production (liters)	Total land (Ha)	Land for milk production (Ha)	Milking cows (n)	Intensity (cows/Ha)
<50	19	125,839	34.8	32.1	29	0.83
50-500	145	846,758	235.3	200.1	163	0.69
≥500	109	3,009,355	1,155.9	797.7	545	0.47
Total	273	1,660,039	588.9	427.0	306	0.52

With regard to milking cows productivity, large farms achieve a level of 5522 lt/cow in the agricultural year, which is superior compared with medium and small farms (5195 lt/cow and 4339 lt/cow respectively).

It seems interesting to analyze some of the socio-economic characteristics of farmers. We found that 63% of farmers are more than 50 years old, while only 4.4% is less than 30 years old. Considering education level, high school was the maximum level achieved for 59% of farmers while 26% have as maximum level of education the University. If we consider the maximum level of education among the three groups defined before, we conclude that farmers in the larger farm size group have a higher level of education than those farmers in the small-size group (40% of farmers went to University in large group while no one went in small group). It is important to note that these results are not applicable for the entire dairy sector where the number of farmers who went to the university is significantly lower. The number of farms which its farmer went to the University represents 11.7% for the entire agricultural sector[7].

Most of the farmers (63%) are full time dedicated in dairy farms. This percentage is higher in smaller farms (73%) which reflect that farmers are more dedicated when farms are small. This result can be expanded to the whole dairy sector in Uruguay where most of small farms are family farmers. In addition, 69% of farmers live in their own farms. As it is expected this percentage is higher in smaller farms (89%) than in larger (55%).

RESULTS AND DISCUSSION

We first estimate the stochastic frontier production function and predict the technical inefficiency effects under the assumption that this inefficiency is identically distributed. This means that technical inefficiency does not depend on farm specific variables. The mean of u_i is invariant across observations (Model 1). In a second stage, we allow the mean of u_i to be a function of farms specific variables that are supposed to explain differences in technical inefficiency among farms. This implies that a specification of a regression model for the technical inefficiency effects in the stochastic frontier is required (Model 2). The parameter estimates of ML method for both frontiers production functions are shown in table 3.

Firstly we estimate model 1 and we use a likelihood ratio test to check if adding the inefficiency term significantly improves the fit of the model. This test compares the stochastic frontier model with the corresponding OLS model where γ is equal to zero. The null hypothesis that OLS better fits the data is rejected at 0.1% significant level. We obtained an estimated γ equal to 0.844, which confirms that both statistical noise and inefficiency are important for explaining deviations from the production function. Hence, stochastic frontier model is more suitable.

In the second stage, we estimate model 2 where we extended the frontier production function including an inefficiency model in order to explain differences in technical inefficiency among farms. The explanatory variables which were included to explain the inefficiency are statistically significant and the estimated average TE in model 2 is higher than in model 1 (0.81 and 0.80 respectively). This implies that the explanatory variables have a negative effect on TI which means a positive effect on TE. Because of all this results, it is possible to conclude that model 2 is more suitable to explain TE among dairy farms.

According to previous results, we focus on the empirical results that were obtained from model 2. We obtained an estimated γ equal to 0.814, which let us conclude that both statistical noise and inefficiency are important for explaining deviations from the production function. However, inefficiency is more important than noise. From this value it could be inferred that the farm specific variability contributes to 81.4% towards the variation in milk production among the dairy farmers, which means that the difference between observed and maximum frontier output can be explained by the difference in farmer's level of TE by adopting different management practices. Besides, it is possible to test the relevance of inefficiency component, using a

[7] General agricultural census 2011. Ministry of Livestock, Agriculture and Fisheries of Uruguay.

likelihood ratio test. The null hypothesis that TI effects are absent ($\gamma = \delta_0 = \delta_1 = \delta_2 = \delta_3 = 0$) and OLS better fits the data is rejected.

As Table 3 shows, all production function coefficients are non-negative meaning that the function satisfies the monotonicity property[8]. The sum over the coefficients of all inputs is 1.10, indicating that the technology has increasing returns to scale. Hence, the increase in milk production is larger than the increase of the inputs quantity that implies an increase of total factor productivity. To confirm this result, we use a likelihood ratio test. The null hypothesis that the production frontier present constant returns to scale ($\beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 = 1$) is rejected at 5% significance level. It might suggests evidence for economies of scale implying that productivity change will depend on improvements in technology and efficiency but also on larger farm size. Although the existence of increasing returns to scale could reflect the current high structure cost that are facing small farmers and their difficulty to overcome it, this result have to be carefully considered due to it may be consequence of some weaknesses that the database presents[9].

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 3, all output elasticities were positive and statistically significant except for the labor. These results reveal that the variables land, cow, feed and pasture influence positively the milk production. This implies that a 1% increase in the percentage of the area that is used exclusively for milk production, herd size, feed consumption and area under cultivated forage results in an estimated increase in milk production of 0.125%, 0.605%, 0.269% and 0.072% respectively. Of all input variables, the number of milking cows had the highest effect on productivity level with elasticity equal to 0.605. One possible reason that could explain the insignificance of labor in the model is that, the information about the number of man hours was not available. This variable was also not significant in the study presented by Bravo-Ureta et al. (2008).

[8] The monotonicity property of a production function says that additional units of an input will not decrease output.

[9] Corss-sectional data; problems in measuring variables.

Table 3: Stochastic Production Frontier Estimates

	Model 1		Model 2	
Variable	Coefficient	SD	Coefficient	SD
Frontier				
Constant	5.736***	0.340	6.347***	0.301
Land	0.134**	0.044	0.125***	0.037
Cow	0.631***	0.049	0.605***	0.044
Labor	0.020	0.032	0.028	0.029
Feed	0.305***	0.030	0.269***	0.028
Pasture	0.072*	0.034	0.072*	0.030
Inefficiency model				
Constant			0.623***	0.078
Insemination			-0.365***	0.109
Vet or agronomic assistance			-0.244**	0.089
Accounting assistance			-0.225*	0.092
σ^2	0.106***	0.017	0.84***	0.022
γ	0.844***	0.076	0.814***	0.077
Log-likelihood	31,05		58,44	
Mean TE	0,80		0,81	

(.), *, **, ***, estimated coefficients significant at the 10%, 5%, 1%, 0.1% respectively.

In terms of technical inefficiency model, a negative sign on a coefficient indicates that an increase in the value of that variable results in a fall in inefficiency; a positive value an increase in inefficiency. The empirical results show that the three explanatory variables that were included have a significant negative impact on technical inefficiency. Holding everything else constant, an increase in the use of artificial insemination, veterinary, agronomic or accounting assistance, is associated with a lower technical inefficiency, implying better efficiency performance. However, the major determinant of efficiency differences is the artificial insemination (-0.365) reflecting that farmers who use this technology are able to achieve higher levels of efficiency than those who are not using artificial insemination.

The mean TE score is 0.811 indicating that on average the sample farmers reached 81.1% of their technical abilities and the remaining percentage were not realized (table 4). This suggests that dairy farmers in Uruguay can improve their productivity and efficiency if they implement more efficient farm practices.

Table 4: Descriptive statistics for estimated TE

Min	Q_1	Median	Mean	Q_2	Max
0.3141	0.7552	0.8438	0.8114	0.9097	0.9593

Analyzing some descriptive statistics for estimated TE, we observe that half of the farmers have a TE level equal to or lower than 0.8438, which is higher than the mean. On the other hand, the maximum TE level is 0.9593, meaning that there are not any farmers that are completely efficient.

As the efficiency has direct effects on the output quantity, it is expected that the efficiency estimates are highly correlated with the output (table 5). A positive and significant correlation

(0.6425) was founded between efficiency and milk production, meaning that the higher the milk production is the more efficient the farmer. This result was also presented by Grau et al. (1995). The correlation is lower (0.462) if we consider the relationship between the farm size, measured as heard size, and efficiency. TE is also positively associated with the total feed consumption. All correlations were significant except for the correlation between efficiency and land variable. A Pearson product-moment correlation coefficient was used to measure the linear correlation between efficiency and the variables. The null hypothesis is that the correlation is equal to zero.

Table 5: Efficiency and explanatory variables correlation

	Milk	Land	Cow	Labor	Feed	Pasture
Efficiency	0.64	-0.04	0.46	0.41	0.51	0.44

The distribution of TE scores for the 273 sampled dairy farms is presented in table 6. As the table indicates, 17.6% of the farms present a level of TE below 70%, while almost 30% of them achieve 90% or more of their technical abilities.

Table 6: Distribution of the farm level measures of technical efficiency (TE)

TE	Farms (n)	Farms in TE group (%)
0-0.49	6	2.2
0.5-0.59	21	7.7
0.6-0.69	21	7.7
0.7-0.79	37	13.6
0.8-0.89	107	39.2
0.9-1	81	29.7
Total	273	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 four groups as table 7 shows. The Bonferroni test is used to analyze differences in average values of each variable between groups. Values sharing same letter between groups are not significantly different at the 5% significance level.

Table 7: Average value of milk production and explanatory variables by efficiency groups

TE farm group	Farms (n)	Milk (lt)	Land (%)	Cows (n)	Labor (n)	Feed (kg)	Pasture (ha)
0-0.79	85	899,240^{a}	84,1^{a}	225^{a}	6^{a}	560,208^{a}	169^{a}
0.8-0.84	58	1,489,715^{ab}	80,5^{a}	307^{ab}	7^{ab}	829,843^{ab}	195^{a}
0.85-0.90	62	1,782,471^{b}	82,2^{a}	314^{ab}	8^{ab}	956,512^{ab}	231^{ab}
0.91-1	68	2,644,684^{c}	81,3^{a}	398^{b}	10^{b}	1,230,427^{b}	309^{b}

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.

With regard to the variable land, the groups have the same letter implying that this variable on average is not significantly different. This means that farmers in the low efficiency group use a similar proportion of land for milk production than the farmers in higher efficiency groups meaning that land variable does not explain differences in TE. However, we find statistically significant differences between groups when we observe the rest of the explanatory variables.

Herd sizes is statistically different comparing the higher and lower efficient farms, indicating that larger farms, in terms of milking cows, achieve a higher efficiency level than smaller. The difference is not significant considering medium efficiency groups.

Labor, feed and pasture are also statistically different when we compare high and low groups. 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.

As can be seen in table 8, there is no doubt about the association between milking cow productivity and efficiency. It is statistically different across the TE farm groups indicating that milking cow productivity improvement seems necessary to achieve higher levels of efficiency. On the other hand, milk production per hectare of land that is used exclusively for milk production, is significantly different if we compare lower and higher efficiency group. However, the difference is not statistically different comparing the two higher efficiency groups which might suggest a weaker association with efficiency.

The number of workers and feed consumption in per cow terms is also statistically different between lower and higher efficiency groups. Hence, higher efficiency farms are larger in terms of the used labor and feed consumption measured in cow terms.

Table 8: Average value of milk production and explanatory variables in per cow terms by efficiency groups

TE farm group	Farms (n)	Milk /cows	Milk /ha	Land[(1)]/cows	Labor/cows	Feed/cows
0-0.79	85	3,737[a]	2,649[c]	1.52[b]	0.044[c]	2,030[c]
0.8-0.84	58	5,009[b]	4,195[a]	1.30[a]	0.030[a]	2,801[a]
0.85-0.90	62	5,768[c]	4,653[ab]	1.37[ab]	0.032[a]	2,918[a]
0.91-1	68	6,651[d]	5,227[b]	1.36[ab]	0.029[a]	2,914[a]

(1) Hectares of land that are used exclusively for milk production.

CONCLUSION

This study estimates a stochastic production frontier and an associated technical inefficiency model to determine the effect of inputs in dairy production and the farm specific characteristics that explain differences in efficiency among dairy farms in Uruguay.

The empirical results showed that the Cobb-Douglas functional form was superior to Translog form and that dairy production exhibits increasing returns to scale. This result might be an insight that there exists a relationship between the size of the farms and the level of milk production, which implies that the level of productivity depends on improvements in technology and efficiency but also on the size of the farm. Although the existence of increasing returns to scale could reflect the current high structure cost that are facing small farmers and their difficulty to overcome it, this result have to be carefully considered due to it may be consequence of some weaknesses that the database presents.

Apart from labor, all input variables were statistically significant and with a positive effect on milk production. The highest effect on production is the number of milking cows followed by feed, land and pasture. The average level of TE in the sample was 81.1%, which suggests that dairy farmers in Uruguay can improve their productivity and efficiency if they implement more efficient farm practices. Farmers could expand milk production using the current level of inputs and technologies already available.

For those farms looking for efficiency gains, the principal determinants of efficiency differences are the use of artificial insemination and veterinary, agronomic or accounting assistance. All these variables have a negative effect on technical inefficiency, implying better efficiency performance. However, the major determinant of efficiency differences is the artificial insemination (-0.365) reflecting that farmers who use this technology are able to achieve higher levels of efficiency than those who are not using artificial insemination.

Overall farm profiles indicate that those in the high efficiency group achieve a higher level of milk production than those less efficient. This result confirms the positive correlation between efficiency and milk production. Although it is true that the high efficiency group contains larger farms, farmers in the low efficiency group use a similar proportion of land for milk production than the farmers in higher efficiency groups meaning that land variable does not explain differences in TE. In terms of efficiency, the measure of size that is important is the number of milking cows, which is statistically different when comparing the higher and lower efficient farms. In addition, 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. With regard to the cow productivity, it was found a direct association with efficiency indicating that milking cow productivity improvement seems necessary to achieve higher levels of efficiency.

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