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Technical Efficiency of the Dual-Purpose Cattle System in Venezuela

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A stochastic production frontier model was estimated to provide standard measurement of technical efficiency of the dual-purpose cattle system located in Zulia State, Venezuela. This system is based on local and low-cost inputs, but has been considered to be inefficient because of its low partial productivity indices when compared with those used in developed countries. Results indicate that the efficiency of this system is reasonably high, downplaying the general idea of inefficiency. Likewise, the efficiency of this system has the potential for improvement through public policies and managerial decisions based on the determinants of technical efficiency.

Key Words: dual-purpose cattle, production frontier, technical efficiency

JEL Classifications: D24, Q12

The dual-purpose cattle system (DPCS) is the traditional cattle production system characteristic of the lowland tropics of Latin American where farmers use crossbred animals (mixture of Zebu, Criollo, and European) to produce milk and meat (Sere and de Vacarro). This system has endured the economic decline that has characterized much of Latin America in the last several decades. DPCS uses local and low-cost inputs as an alternative to the more expensive purebred cow system, often providing the stability and flexibility necessary to buffer economic changes prevailing in developing countries like Venezuela. The DPCS has become the main alternative to supply the milk requirements of tropical countries; it encompasses around 78% of total bovine and 41% of total milk production in the Latin American tropics (Rivas cited by Fernandez-Baca). This system, however, is often considered to be inefficient because of potentially lower partial productivity values (Table 1). Efficiency of this system has been generally measured through partial productivity indices that provide useful information but do not take into account the effect of total inputs on output as a measure of total efficiency. A standard for this system is needed that uses the concept of total factor productivity and indicates how efficient these farmers are given inputs and available technology. Quantifying socioeconomic and technical factors that influence efficiency will help in directing public policies to improve efficiency.

Characteristics of the DPCS in Latin America

Generally, dual-purpose cattle systems (DPCSs) are located between the Tropic of Cancer and the Tropic of Capricorn and approximately 1,500 m above sea level (Sere and de Vaccaro). Most DPCS farms are

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Table 1. DPCS Productivity Indices

Concept	Average[a]	Range
Milk production per cow-day (kg)	4.0	2.8–6.5
Milk production per lactating period (kg)	1,180.0	749–1,584
Lactating period (day)	290.0	244–311
Calving rate (%)	64.0	39–81
Age at first calving (months)	37.0	32–43
Calf mortality (%)	13.0	2–24
Stocking rate (AU[b] ha^{-1})	1.4	0.72–1.9
Milk production (kg ha^{-1}-yr^{-1})	476.0	182–749
Beef production (kg ha^{-1}-yr^{-1})	116.0	45–192

Source: Pearson de Vaccaro.

[a] Unweighted productivity indices of studies for eight countries: Bolivia, Brazil, Colombia, Costa Rica, Honduras, Mexico, Panama, and Venezuela.

[b] AU is animal unit.

located in the lowlands where the drainage can be deficient, depending on soil textures. Rainfall is seasonal and erratic with precipitation oscillating from 800 to 3,500 mm per year, and a dry season can range from 2 to 7 months. Average temperature oscillates between 20 and 28 °C.

Under a DPCS, cows are not specialized in milk production (i.e., used primarily beef cows) but are used for milk with Zebu or a crossbred of Zebu and Criollo being the most common breed (Seré and de Vaccaro). In Venezuela this dual-purpose cattle system, mainly located in Zulia State, provides more than 70% of the milk and more than 30% of beef production nationally (Fernández).

In Zulia State the average farm size is around 300 ha and 400 head, and the owner-manager is literate. Labor is hired drawing from a neighboring country (Colombia) or from native Indians called *guajiros.* The labor supply is unstable and subject to high turnover. While the most common breeding method is natural uncontrolled breeding, artificial insemination and natural controlled breeding have become a common practice in recent years. Along with the use of natural controlled breeding and artificial insemination there is a tendency to use periodical vaccinations to control foot and mouth disease, brucellosis, septicemia, and endo- and ecto-parasites. Pasture fertilization is not a common practice; only 20% of the farmers apply fertilizer. Weed control is done irregularly using manual, chemical, and mechanical controls. Milk contributes to around 70% of total farm revenue. Few producers keep accounting and technical records (Fernández). Given the diversity in animal and feeding management, the question of technical efficiency is paramount.

Technical Efficiency

A producer is considered efficient if a higher output cannot be obtained from a given set of inputs and technology (i.e., technical efficiency) and if this output cannot be produced at a lower cost (i.e., allocative or price efficiency) (Greene 1997). Different approaches have been used to measure efficiency and productivity such as the index number, least square econometric methods, or stochastic frontiers functions, among others. The index approach is based on the use of partial and total factor productivity indices. The disadvantage of this approach is that it assumes that observed output is the frontier or best practice, but it ignores inefficiency, technical and allocative (Grosskopf). Frontier functions (production, cost, revenue. and profit) have been estimated using different methods; data envelopment analysis (DEA) and stochastic frontiers are the most used in empirical works. DEA is based in mathematical programming, and stochastic frontiers generally use econometrics models. Coell, Rao, and Battese suggest that the stochastic frontiers approach performs better than DEA with agricultural data because the data often include serious measurement error and environmental effects, particularly if the data come from developing countries. Likewise, they indicate that the stochastic frontier approach performs well for single-output technologies. However, in the case of multiple outputs, it can be used if cost minimization is assumed as a behavioral objective, or if enough information about output prices is available, allowing the aggregation of multiple outputs into a single measure (Coelli, Prasada Rao, and Battese). An alternative approach to consider for multiple outputs is the use of distance functions, but potential complications with input endogeneity could arise (Kumbhakar and Lovell). However, Coelli pointed out that production functions also do not escape from this criticism. In this research the stochastic production frontier approach will be used.

Frontier efficiency models begin with the work of Farrell, where he decomposed economical efficiency into technical efficiency (TE) and allocative efficiency, using unit isoquants and assuming constant returns to scale (Fφrsund, Lovell, and Schmidt). Econometric frontier models are generally classified as deterministic or stochastic models, with the deterministic frontier models measuring inefficiency through the error term considering only one side of the model error (u). Following Greene (1997), if a production frontier like $y_i = f(x_i,\beta)TE_i$ is assumed, technical efficiency can be expressed as a ratio between $y_i/f(x_i,\beta)$, which represents the total factor productivity. The values of TE_i are between 0 and 1; β is the vector of coefficient of inputs x_i; and i refers to the firms in the sample. Taking logs, this model becomes linear:

$$(1) \quad \begin{aligned} \ln y_i &= \ln f(x_i,\beta) + \ln TE_i \\ &= \ln f(x_i,\beta) - u_i, \end{aligned}$$

where u_i should be greater than zero. Since $u_i = -\ln TE_i$, $TE_i = \exp(-u_i)$, where u_i represents the deviations from the frontier function, and u_i is assumed to be identical and independently distributed with a nonnegative mean and finite variance.

Stochastic Frontier

The stochastic frontier approach proposed by Aigner, Lovell, and Schmidt and Meeusen and Broeck differs from the deterministic statistical approach in that the error term is decomposed into random error (v) and one-sided error (u) terms. A one-sided error represents the inefficiency of firms, and the random error (both sides) represents the random effect uncontrolled by the firms. Thus, the general formulation can be expressed as

$$(2) \quad y_i = f(x_i,\beta)\exp^{\varepsilon_i},$$

where $\varepsilon_i = v_i - u_i$; v_i is unrestricted and usually represents a normally distributed random error and u_i is the same as defined earlier. Both components of the error term are considered to be independent and identically distributed (iid) across observations. Equation (2) can be rewritten as

$$(3) \quad y_i = f(x_i,\beta)\exp^{v_i} TE_i,$$

where TE_i can be defined as the ratio between $y_i/f(x_i, \beta)\exp^{v_i}$ and y_i represents the observed output. Now, $f(x_i, \beta)\exp^{v_i}$ is the stochastic production frontier, with $f(x_i,\beta)$ being the deterministic part and $\exp^{v_i}$ the random effect (Kumbhakar and Lovell). Taking the natural log of Equation (3) gives

$$(4) \quad \ln y_i = \ln f(x_i,\beta) + v_i - u_i.$$

The estimation of u_i in this case should be made indirectly by considering the mean or the mode of its conditional distribution $[u_i \mid v_i - u_i]$ (Jondrow et al.).

To calculate the one-sided component of the error (u_i), several distributions have been assumed, such as half-normal, exponential, truncated normal, or gamma distributions. Empirically each one has led to different results for sample mean efficiencies (Baccouche and Kouki; Greene 1990). However, Mbaga et al. found that not only the distribution of the one-sided error but also the functional form of the production frontier is not a determinant of the ranking of the efficiency values. Similarly Kumbhakar and

Lovell point out that there is no concrete evidence indicating that the ordinal rank of the efficiency scores is sensitive to the distribution of one-sided error.

Different functional forms have also been used to analyze farm efficiency; the Cobb-Douglas functional form is most often used. Giannakas, Tran, and Tzouvelekas reported that the estimates of production frontier and the technical scores were sensitive to the functional specification when comparing translog, normalized quadratic, squared-root quadratic, generalized Leontief, nonhomothetic CES, and Cobb-Douglas functions. As indicated by Schmidt and Greene (1997), more flexible functional forms avoid distortion and yield higher efficiency measures. Greene (1997) found collective statistical significance for 15 coefficients when translog and Cobb-Douglas production functions were compared, but the changes in the estimators were relatively minor. Kopp and Smith and Baccouche and Kouki also concluded that the impact on the efficiency indexes was small when they compared different functional forms for the production frontier (Cobb-Douglas, CES, and translog). Likewise, Bauer pointed out that as we move away from the Cobb-Douglas functional form, estimation becomes more complicated.

Determinants of Technical Efficiency

The technical inefficiency values estimated using the Jondrow et al. technique are regressed against a set of socioeconomic and technical variables (z_i) that are expected to influence TE. Equations 5 and 6 (Kumbhakar and Lovell) show this two-step approach:

$$(5) \quad \ln y_i = \ln f(x_i, \beta) + v_i - u_i,$$

$$(6) \quad \mathrm{E}(u_i/z_i) = \gamma z_i + \varepsilon_i,$$

where all the variables have been previously defined except for z_i, which represents a vector of socioeconomic and technical variables, and γ is a vector of the coefficients for these explanatory variables.

An alternative approach proposed by Kumbhakar, Ghosh, and McGuckin is to estimate the coefficients of the production frontier and the determinants of technical inefficiency in one step. In this case the determinants of the inefficiency values are incorporated into the one-sided error where Equation (8) is substituted into Equation (7), and then the coefficients are estimated in one step, unlike the method used for estimating in Equations (5) and (6):

$$(7) \quad \ln y_i = \ln f(x_i, \beta) + v_i - u_i,$$

$$(8) \quad u_i = \gamma z_i + e_i,$$

where e_i is the random error. The argument for this approach revolves around the premise that if the socioeconomic and technical explanatory variables affect efficiency directly, then they should be included in the production frontier for the estimates of the production frontier parameters and the technical efficiency scores to be consistent. Utilization of the standard regression step is not appropriate because the dependent variable is bounded by zero and one. Also, the meaning of the residual is less clear in the regression step (Kumbhakar, Ghosh, and McGuckin; Kumbhakar and Lovell). Advocates of the first approach indicate that if the socioeconomic and technical variables explain the variation in efficiency and do not have a direct impact on the structure of the production frontier, the two-step approach can be used (Kalirajan). McCarty and Yaiswarng compared the two approaches and concluded that either or both approaches might be appropriate depending on the hypothesis of the research to be answered.

Dual-Purpose Cattle System Production Frontiers

Using a farm survey conducted by the Unidad Coordinadora de Proyectos Conjuntos (UCPC), University of Zulia, Venezuela, the stochastic frontier production function and technical efficiency values were estimated for 123 farms. Changes in the technical efficiency were considered across socioeconomic and technical variables as well as location and farm size. A stochastic production frontier approach was used to calculate the partial output elasticities and to define technical efficiency of the Venezuelan farms. The general model can be expressed as

(9) $y_i = f(x_i,\beta)\exp^{\varepsilon_i}$,

where $\varepsilon_i = v_i - u_i$; y_i is output of the ith farm, x_i is a vector of inputs, β is the vector of parameters, u_i represents one-sided error, and v_i is the random error. The dependent variable that represents output (y_i) is measured using gross revenue to aggregate the different outputs of farms because the data do not permit the desegregation of inputs according to outputs.

The explanatory variables (vector x_i) in these models follow the inputs present in the cost and capital structure of this system established by UCPC, such as labor (*LE1*), capital in pastures (*LCP*), capital in land (*LCL*), capital in buildings (*LCE*) and capital in machinery (*LCM*),[1] capital in cattle (*LCC*), machinery repairs and parts (*LJ3*), veterinary medicine (*LI6*), seeds (*LI2*), fertilizer (*LI3*), herbicide and pesticide (*LI4*), supplement feed (*LI5*), gas and lube (*LI7*), machinery rental (*LJ2*), building maintenance (*LJ4*), taxes and insurance (*LJ5*), utilities (*LJ6*), and miscellaneous (*LJ7*). The different types of capital were not aggregated in order to know the individual impact on production (marginal effect) because little information is available for this system. Except for labor, which is measured in person-year equivalents, all other variables are measured in monetary terms (Bolivares) because of limitations of the data to create physical measures of some variables. Using monetary measures to estimate production functions is not an exception; generally they are used to overcome deficiencies of the data and to integrate different types of inputs into one category where difficulties exist in creating physical variables (Bagi; Tauer and Belbase). In addition, the use of value measures allows the adjusting of inputs and output by quality across farms because the price should reflect quality differences. This condition, the homogeneous quality of inputs, is necessary to estimate production functions. For example, measuring land in monetary terms (Bs) instead of physical terms (ha) accounts for not only differences in soil across farms but also environmental variables[2] such as rainfall that are generally embedded in the price of the land. Differently from poultry and swine farms that are generally located close to urban areas, land prices of cattle farms in Zulia State usually do not reflect the pressure of urban and industrial growth. Likewise, development of a physical measure of forage intake per farm in a system based on grazing will be difficult because it will depend on many factors such as forage and cattle management. Nevertheless, a measure of the effective amount of hectares of forage available to graze across farms will be a proxy variable to measure the supply of pasture.

In this research capital in pasture represents the aggregate market value of the different types of pastures across farms based on the effective pasture area of each farm. Similar justifications apply to the other inputs such as fertilizer, veterinary medicine, herbicide and pesticide, capital in machinery, capital in cattle, and supplement feed.

Dual-purpose cattle farmers are characterized by the use of a pool of technology practices such as breeding techniques, weed control, pasture and grazing methods (continuous or alternate rotational grazing), and fertilization that makes it difficult to classify

[1] Annualized flows of capital assets were not considered because some assets of the farm have been fully depreciated.

[2] Environmental variables are possible sources of input endogeneity in production functions that could bias downward TE estimates. To minimize this effect some sample restriction were imposed: a) farms had to be consolidated (developed farms), b) production had remained stable over the last three years (no major variations), c) the weather conditions for the year studied had to be typical (farms that suffered flooding, fires, or legal problems were not surveyed), and d) the manager of the farms should have had more than one year on the farm. Although these restrictions could not guarantee total absence of endogeneity, they make it much less likely. We did not see any indications of input endogeneity among the explanatory variables. Some variables were correlated, but this problem was fixed using the principal components approach.

producers according to a homogeneous set of technology, even if a large amount of data are available. One production function was developed in this study representing the production frontier relative to the best practices because of limitations on quality and quantity of data. Limitations of the data occurred, for example, in the use of artificial insemination; the data in this case indicate only the number of farmers currently using this practice but do not reflect if other farmers have used this practice in previous years. In addition, the data do not provide information about the type and degree of breeding. Another example illustrating limitations in the quality of the data is fertilization practice. Data on fertilization practices from previous years were not available, leaving room for possible residual fertilizer effects reflected in the current evaluation. Same situations apply for weed control and other technological practices. Values of these variables are not nested in one region relative to another since the regions are contiguous with very similar cultures.

A Cobb-Douglas functional form was selected over the translog function to avoid degree-of-freedom problems. The Cobb-Douglas frontier function after taking the natural logarithm of Equation (10) is

$$\ln y_i = \ln f(x_i,\beta) + v_i - u_i. \tag{10}$$

The coefficients for the stochastic frontiers (10) were calculated using maximum likelihood (ML) following Aigner, Lovell, and Schmidt methodology. Several distributions of the one-sided error were considered (half-normal, exponential, and truncated), but the final model was limited to the half-normal distribution[3] to achieve convergence in the log likelihood function. Several authors have noted difficulties using other distributions with smaller samples sizes similar to the 123 farms in this analysis.

Following Kumbhakar and Lovell, the log likelihood function for the normal–half-normal distribution for a sample of n observations is

$$\ln L = const - n\ln\sigma + \sum_i \ln\Phi\left(-\frac{\varepsilon_i\lambda}{\sigma}\right) - \frac{1}{2\sigma^2}\sum_i \varepsilon_i^2, \tag{11}$$

where $\Phi(.)$ is the cumulative distribution function for a standard normal random variable, $\varepsilon_i = \ln y_i - \ln f(x_i, \beta)$, $\lambda = \sigma_u/\sigma_v$, and $\sigma^2 = \sigma_u^2 + \sigma_v^2$.

To compare and rank the relative importance of the exogenous variables, standardized coefficients were also derived (i.e., $\widehat{\beta}_j^* = \widehat{\beta}_i\sigma_{x_j}/\sigma_y$). Some variables showed a high degree of correlation such as labor, different classifications of capital (pasture, land, machinery, buildings, and cattle), machinery repairs and parts, and veterinary medicine. The model was estimated using the principal component, and then coefficients for the original variables were derived from the parameters estimated from the appropriate principal components. Since this is a standard procedure, the details are omitted. The econometric software package Time Series Processor (TSP) version 4.5 was used to perform the statistical calculations.

Technical Efficiency Specifications

Technical inefficiency values were estimated using the Jondrow et al. technique. Following Kumbhakar and Lovell's notation, the mean for the one-sided error (u_i) for the half-normal distribution was calculated where

$$E(u_i|\varepsilon_i) = \frac{\sigma\lambda}{(1+\lambda^2)}\left[\frac{\phi(\varepsilon_i\lambda/\sigma)}{1-\Phi(\varepsilon_i\lambda/\sigma)} - \left(\frac{\varepsilon_i\lambda}{\sigma}\right)\right]. \tag{12}$$

Then technical efficiency values were calculated using the expected residuals from Equation (12):

$$TE_i = \exp^{-E(u_i|\varepsilon_i)}. \tag{13}$$

[3] One-step estimation using a truncated distribution was addressed, but the convergence of the log likelihood function was not achieved. The exponential model did converge, and the results were similar to the half-normal distribution. Because the primary focus is to deal with estimating technical efficiency and because empirical results from both models are similar, subsequent analysis will draw for only the half-normal results.

DPCS Determinants of Technical Efficiency

The two-step approach was used to define and quantify the determinants of technical efficiency in the dual-purpose cattle system. Given that technical efficiency is bounded between zero and one, a logistic function was used when linking efficiency to both the socioeconomic and technical variables as suggested with z_i in Equations (14) and (15):

$$(14)\quad TE_i = \frac{1}{(1 + \exp^{\gamma z_i + \varepsilon_i})},$$

$$(15)\quad \ln\left(\frac{1}{TE_i} - 1\right) = \gamma z_i + \varepsilon_i,$$

where all terms have been described previously.

Thirteen socioeconomic and technical variables were identified as factors hypothesized to influence *TE* (Table 2). Most of these variables are categorical except for liters per milker and stocking rate, which were included in the models as continuous variables. Let $w_i = \ln[(1/TE_i) - 1]$, then the model in Equation (16) explicitly captures the z_i variables noted in Table 2:

$$\begin{aligned}(16)\quad w_i = {} & \gamma_0 + \gamma_2 DPEDU_i + \gamma_4 DPEXP_i \\ & + \gamma_6 DPPER_i + \gamma_8 CRED_i \\ & + \gamma_{10} DSUG21_i + \gamma_{11} DSUG31_i \\ & + \gamma_{12} DSUG41_i + \gamma_{14} Z21_i + \gamma_{15} Z31_i \\ & + \gamma_{16} Z41_i + \gamma_{18} PSYST2_i \\ & + \gamma_{19} PSYST31_i + \gamma_{21} PROD21_i \\ & + \gamma_{22} PROD31_i + \gamma_{23} PROD41_i \\ & + \gamma_{24} PROD51_i + \gamma_{26} DBRED_i \\ & + \gamma_{28} DTEN_i + \gamma_{30} DTECHN_i \\ & + \gamma_{31} LTMILKER_i + \gamma_{32} LTMILKSQ_i \\ & + \gamma_{33} CARGANEF_i + \varepsilon_i,\end{aligned}$$

where γ_0 represents the average technical efficiency, $DPEDU_i = EDU2_i - EDU1_i$; $DPEXP_i = EXP2_i - EXP1_i$; $DPPER_i = PER2_i - PER1_i$; $CRED_i = CRED2_i - CRED1_i$; $DSUG21_i = SUG2_i - SUG1_i$; $DSUG31_i = SUG3_i - SUG1_i$; $DSUG41_i = SUG4_i - SUG1_i$; $Z21_i = Z2_i - Z1_i$; $Z31_i = Z3_i - Z1_i$; $Z41_i = Z4_i - Z1_i$; $PSYST21_i = PSYST2_i - PSYST1_i$; $PSYST31_i = PSYST3_i - PSYST1_i$; $PROD21_i = PROD2_i - PROD1_i$; $PROD31_i = PROD3_i - PROD1_i$; $PROD41_i = PROD4_i - PROD1_i$; $PROD51_i = PROD5_i - PROD1_i$; $DBRED_i = BRED2_i - BRED1_i$; $DTEN_i = TEN2_i - TEN1_i$; *and* $DTECHN_i = TECHN2_i - TECHN1_i$.

The coefficients for the different categorical variables represent the deviation of each variable relative to the average farm (γ_0), averaged over all the characteristics. For example, the effect of education (*EDU1*) is $\gamma_0 - \gamma_2$ and *EDU2*, $\gamma_0 + \gamma_2$. The impact of variables with more than two levels follows in a similar way where, for example, farm size is depicted by three categories: *SUG1* is $\gamma_0 - \gamma_{10} - \gamma_{11} - \gamma_{12}$; *SUG2*, $\gamma_0 + \gamma_{10}$; *SUG3*, $\gamma_0 + \gamma_{11}$; and *SUG4* impacts are $\gamma_0 + \gamma_{12}$. A similar procedure was used for the other variables.

DPCS Frontier Estimates

Estimates for the production frontiers, their respective coefficients (output partial elasticities), standardized coefficients, and *t*-statistics are shown in Table 3. The positive signs for most of the coefficients were expected. Fertilizer (*LI3*), an input promoted by the extension service to increase productivity of dual-purpose cattle system, had no significant effect on production. Inputs addressed to increase animal productivity, such as supplement feed, labor, and veterinary medicine, were the inputs with more significant effect on the dependent variable; while inputs addressed to increase land productivity (fertilizer, seed, herbicide, etc.) did not have a significant impact on production. In this system the production is given by the interaction between animal productivity (kg of milk per cow) and land productivity (cows per ha) because it is based on grazing of improved pasture. Tropical pastures are characterized by low nutritive value with crude protein and digestibility levels ranging from 4% to 8% and 50% to 60%, respectively. Such pasture quality bounds milk production per cow to levels below 6 or 7 L per cow per day when pastures are not fertilized. Similarly, consumption of forage dry matter tends to decrease when

Table 2. Socioeconomic and Technical Variables

Variable	Description	Value (1 = yes; 0 = otherwise)	Hypothesis
EDU1	Illiterate or only read and write	0, 1	$\gamma_0 - \gamma_2 > 0$
EDU2	Elementary school or higher education	0, 1	$\gamma_0 + \gamma_2 > \gamma_0 - \gamma_2$
EXP1	Five years of experience or less	0, 1	$\gamma_0 - \gamma_4 > 0$
EXP2	More than five years of experience	0, 1	$\gamma_0 + \gamma_4 > \gamma_0 - \gamma_4$
PER1	Presence on the farm less than twice a week	0, 1	$\gamma_0 - \gamma_6 > 0$
PER2	Presence on the farm twice a week or more	0, 1	$\gamma_0 + \gamma_6 > \gamma_0 - \gamma_6$
TEN1	County and government land	0, 1	$\gamma_0 - \gamma_{28} > 0$
TEN2	Private land	0, 1	$\gamma_0 + \gamma_{28} > \gamma_0 - \gamma_{28}$
CRED1	Farmer that does not use credit	0, 1	$\gamma_0 - \gamma_8 > 0$
CRED2	Farmer that used credit in the last 10 years	0, 1	$\gamma_0 + \gamma_8 > \gamma_0 - \gamma_8$
SUG1	Farm size less than 300 ha	0, 1	$\gamma_0 - \gamma_{10} - \gamma_{11} - \gamma_{12} > 0$
SUG2	Farm size from 300 to 400 ha	0, 1	$\gamma_0 + \gamma_{10} > \gamma_0 - \gamma_{10} - \gamma_{11} - \gamma_{12}$
SUG3	Farm size between 400 and 575 ha	0, 1	$\gamma_0 + \gamma_{11} > \gamma_0 + \gamma_{10}$
SUG4	Farm size greater than 575 ha	0, 1	$\gamma_0 + \gamma_{12} < \gamma_0 + \gamma_{11}$
Z1	South part of Zulia State	0, 1	$\gamma_0 - \gamma_{14} - \gamma_{15} - \gamma_{16} > 0$
Z2	Eastern part of Zulia State	0, 1	$\gamma_0 + \gamma_{14} < \gamma_0 - \gamma_{14} - \gamma_{15} - \gamma_{16};\ \gamma_0 + \gamma_{15};\ \gamma_0 + \gamma_{16}$
Z3	Western part of Zulia State	0, 1	$\gamma_0 + \gamma_{16};\ \gamma_0 + \gamma_{14} < \gamma_0 + \gamma_{15} < \gamma_0 - \gamma_{14} - \gamma_{15} - \gamma_{16}$
Z4	Northwestern part of Zulia State	0, 1	$\gamma_0 + \gamma_{14} < \gamma_0 + \gamma_{16} < \gamma_0 - \gamma_{14} - \gamma_{15} - \gamma_{16};\ \gamma_0 + \gamma_{15}$
PSYST1	Cow-calf production system	0, 1	$\gamma_0 - \gamma_{18} - \gamma_{19} > 0$
PSYST2	Cow-yearling production system	0, 1	$\gamma_0 + \gamma_{18} > \gamma_0 - \gamma_{18} - \gamma_{19}$
PSYST3	Cow-steer production system	0, 1	$\gamma_0 + \gamma_{19} > \gamma_0 + \gamma_{18}$
PROD1	Milk production per cow equal to or less than 1,000 L	0, 1	$\gamma_0 - \gamma_{21} - \gamma_{22} - \gamma_{23} - \gamma_{24} > 0$
PROD2	Milk production per cow between 1,000 and 1,500 L	0, 1	$\gamma_0 + \gamma_{21} > \gamma_0 - \gamma_{21} - \gamma_{22} - \gamma_{23} - \gamma_{24}$
PROD3	Milk production per cow between 1,500 and 2,000 L	0, 1	$\gamma_0 + \gamma_{22} > \gamma_0 + \gamma_{21}$
PROD4	Milk production per cow between 2,000 and 2,500 L	0, 1	$\gamma_0 + \gamma_{23} > \gamma_0 + \gamma_{22}$
PROD5	Milk production per cow higher than 2,500 L	0, 1	$\gamma_0 + \gamma_{24} > \gamma_0 + \gamma_{23}$
BRED1	Producers using natural breeding	0, 1	$\gamma_0 - \gamma_{26} > 0$
BRED2	Producers using artificial insemination	0, 1	$\gamma_0 + \gamma_{26} > \gamma_0 - \gamma_{26}$
TECHN1	Frequency of technical assistance less than once a month	0, 1	$\gamma_0 - \gamma_{30} > 0$
TECHN2	Frequency of technical assistance once a month or higher	0, 1	$\gamma_0 + \gamma_{30} > \gamma_0 - \gamma_{30}$
LTMILKER	Liters per milker-year	> 0	$\gamma_{31} > 0;\ \gamma^2_{32} < 0$
CARGANEF	Stocking rate (Animal unit per hectare)	> 0	$\gamma_{33} > 0$

Table 3. Production Frontier Estimates

Variable	Coefficient	*t*-Statistic	Standardized Coefficient
Intercept	3.6533		
LEI (Labor)	0.2306*	19.3962	0.2168
LCP (Capital in pastures)	−0.0184	−0.7153	−0.0243
LCL (Capital in land)	0.1198*	10.6500	0.1284
LCE (Capital in buildings)	0.0163	0.5002	0.0132
LCM (Capital in machinery)	0.0495*	2.8638	0.0524
LCC (Capital in cattle)	0.2612*	18.6679	0.2576
LI6 (Veterinary medicine)	0.3016*	14.8006	0.3234
LI2 (Seed)	0.0031	1.1173	0.0264
LI3 (Fertilizer)	−0.0036	−1.1479	−0.0251
LI4 (Herbicide and pesticides)	0.0019	0.7541	0.0165
LI5 (Supplement feed)	0.0715*	4.5155	0.1172
LI7 (Gas and lube)	0.0057	0.6784	0.0160
LJ2 (Machinery rental)	0.0036	0.9576	0.0223
LJ3 (Machinery repairs and parts)	−0.0038	−0.9391	−0.0243
LJ4 (Building maintenance)	0.0080**	2.4036	0.0607
LJ5 (Taxes and insurance)	0.0106**	2.4625	0.0599
LJ6 (Utilities)	0.0059	0.3835	0.0111
LJ7 (Miscellaneous)	−0.0055***	−1.6813	−0.0432
Lambda	1.6926	1.4851	1.1397
Sigma	0.2975*	5.2591	0.0566
Log likelihood	15.1381		

* $P \leq 0.01$; ** $0.01 < P \leq 0.05$; *** $0.05 < P \leq 0.10$.

crude protein values are less than 6% or 8%, limiting production (González). To compensate for this problem, producers usually use feed supplements to increase production. This variable, supplement feed, showed a significant effect on production, unlike capital in pasture variable, which was not significant. Kumbhakar, Ghosh, and McGuckin used levels of crude protein of forage as an input in stochastic frontier for U.S. dairy farms and did not find significant impacts, further dropping this variable from the model.

DPCS Technical Efficiency Values

Technical efficiency as estimated with Equation (16) and reported in Figure 1 is shown to be a function of both demographics and technical characteristics for each farm. Both sets for characteristics are indicative of the cross section of farmers in the Zulia regions, and hence the range of technical efficiencies is going to differ across these characteristics. This gives direct insight into the extent of the efficiency problem. If all technical efficiency levels were high and showed little change, there would be no problems. Whereas a wide range of technical efficiency values points to the extent of the problem and the potential for improvements using the appropriate policy instruments.

In Figure 1 farms have been ranked from the most to the least efficient and then expressed as a percentage of the total number of farms. Technical efficiency ranges from .94 to .57 based on the stochastic model, producing nearly a 40% drop in technical efficiency between the most and least efficient farms. Clearly there is a substantial difference across the farms, suggesting the need for proactive policies to address the decline in efficiency over the set of farm characteristics. Figure 1 is particularly useful for showing the extent of the efficiency problem when expressing the farms on a percentage basis. After arranging the farms according to their estimated efficiency levels in declining order of efficiency, 25% of the farms show a technical

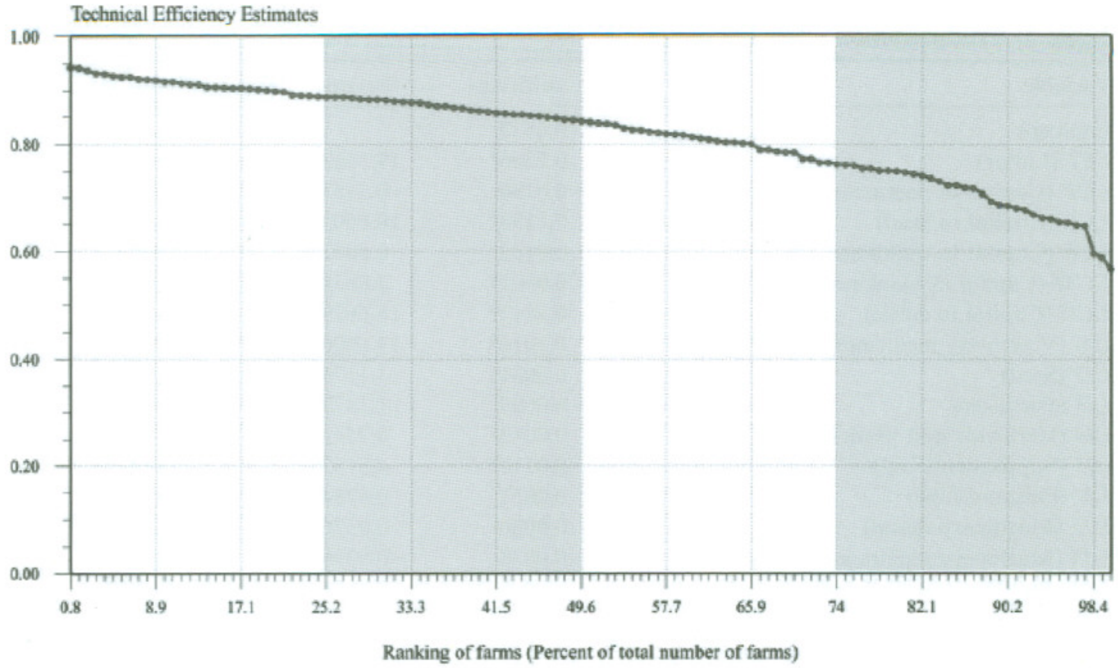

Figure 1. Ranking the Levels of Technical Efficiency among 123 Venezuela Farms

efficiency level of at least .89. Yet 75% have efficiency levels below .89. Between the 25–50% range of farms, technical efficiency drops from .89 to .84 or only .04 points. From the 50% to 75% range of farms, the level drops to .76. For the least efficient farms beyond the 75% level, efficiency drops from .76 to .57. Clearly the major loss in technical efficiency is among those farms in the last group where the decline in technical efficiency drops off rapidly. Knowing the combination of demographic and technical characteristics among those farms in this last group (i.e., beyond the .75 level) points to potential areas to focus for policy purposes, educational programs, and assistance.

The average technical efficiency, estimated to be .765, could be considered high but susceptible to improvement, especially for the least efficient farmers, where the efficiency level drops 19 percentage points from the average.

Determinants of Technical Efficiency

Results from the logistic function (Equation 16) can be seen in Table 4. The model explained approximately 50% of total variation in technical efficiency. Most estimates were different from zero at a high significance level (see *t*-values). The coefficients showed the expected sign except for education (*DPEDU*) and breeding system (*DBRED*), but they were not significant. Similarly, coefficients for land tenure (*DTEN*) and stocking rate (*CARGANEF*) were not different from the average technically efficient farm.

The variables experience (*DPEXP*), owner presence (*DPPER*), farm size (*DSUG*), location (*Z31*), production system (*PSYST31*), milk production per cow (*PROD21* and *PROD41*), and liter per milker (*LTMILKER*) were significant at the 90% or higher level with respect to the average technically efficient farm. But milk production per cow (*PROD51*), credit (*CRED*), and frequency of technical assistance (*DTECHN*) were only significant for a one-tail test.

Evaluation of the Determinants of Technical Efficiency and Policy Implications

Simulation results (Figure 2) show an average farm technical efficiency of 0.765; this value

Table 4. Estimates of the Determinants of Technical Efficiency

Variable	Variable Name	Coefficient	t-Statistic	Standardized Coefficient
C	Intercept	−0.2296	−0.7427	
DPEDU	Education	0.0384	0.4439	0.0483
DPEXP	Experience	−0.2826	−2.0114**	−0.1708
DPPER	Presence	−0.1695	−2.1497**	−0.1896
CRED	Credit	0.0808	1.5157****	0.1277
DSUG21	Size	0.4687	2.7633*	0.5050
DSUG31	Size	−0.6261	−3.7332*	−0.6282
DSUG41	Size	0.2689	1.7680***	0.3248
Z21	Location	0.1064	0.9373	0.1256
Z31	Location	−0.2601	−1.9906**	−0.3272
Z41	Location	0.0182	0.1994	0.0230
PSYST21	Production system	0.0785	1.1293	0.1019
PSYST31	Production system	−0.2892	−2.8029*	−0.3883
PROD21	Cow productivity	0.2541	2.3148**	0.2688
PROD31	Cow productivity	−0.0894	−1.0074	−0.0899
PROD41	Cow productivity	−0.2543	−2.0272**	−0.2071
PROD51	Cow productivity	−0.3843	−1.7872***	−0.2203
DBRED	Breeding system	0.0489	0.6921	0.0730
DTEN	Land tenure	0.0554	1.0548	0.0896
DTECHN	Technical assistance	−0.0956	−1.7072***	−0.1587
LTMILKER	Labor productivity	−0.0289	−4.2998*	−1.1705
LTMILKSQ	Labor productivity squared	0.0001	3.5906*	1.1154
CARGANEF	Stocking rate	−0.0004	−0.3444	−0.0408
F		3.8477		
R^2		0.4990		
Adj. R^2		0.3693		
Log likelihood		−61.1130		
N of Obs.		108.0000		

* $P \leq 0.01$; ** $0.01 \leq P \leq 0.05$; *** $0.05 \leq P \leq 0.10$; **** $0.05 \leq P \leq 0.10$ for a one-tail test.

was obtained by the addition of the intercept term and the mean values of liters per milker, liters per milker squared, and stocking rate multiplied by their respective coefficients. In Figure 3 factors affecting technical efficiency are arranged according to their impacts with the impacts expressed relative to the average level of technical efficiency. In the right portion of this figure, the absolute range of change in technical efficiency is illustrated; e.g., for farm size the maximum range is .19 and is the largest factor. Differences in farm size clearly have the greatest impact on technical efficiency with values from a low of .67 to a high of .86 across the farm sizes. Farm size between 400 and 575 ha (*SUG3*) had the highest efficiency values with a technical efficiency of .86 or 10 percentage points above the average. Note the significant drop in efficiency from the midsize and largest farms relative to the 400–575 ha farm size. This was surprising but clearly indicates that there are no trends in efficiencies moving across farm size. These results do point to the potential loss in efficiency with public policies that would break up the farms in the 400–575 ha size. The average farm size was around 300 ha, and the greatest gain in efficiency would occur with the expansion of these farms to the next largest size (400–575 ha) as seen in Figure 2.

Milk production per cow is the second largest factor affecting TE. Compared to the average farm, 6–8% changes in technical efficiency were reached for levels of production of 2,000–2,500 L and more than 2,500 L, respectively. Considerable efficiency gains could be achieved if producers use animals with higher production levels while

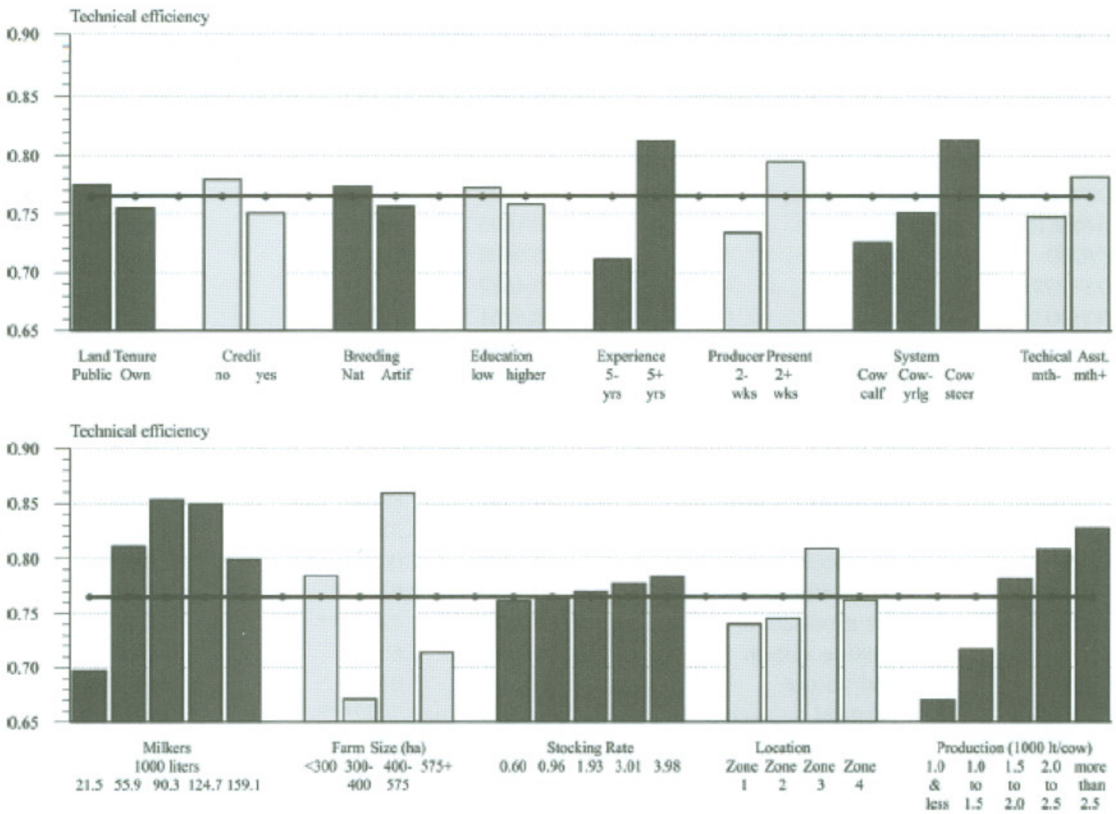

Figure 2. Impact of Socioeconomics and Technical Variables on Technical Efficiency of DPCS

still using breeds that adapt to the tropical environment, mainly considering that around 50% of farmers have production levels per cow of less than 1,500 L.

Labor productivity (liters per milker) had a positive impact on technical efficiency, presenting a significant quadratic relationship. A 12% increment in efficiency relative to the average farm could be possible if farmers use the labor efficiently.

These three factors address mostly production practices, and they have by far the greatest impact on technical efficiency (Figure 3). However, producer experience is also particularly important. Farmers with more than five years of experience were approximately 14% more efficient than farmers with less than five years of experience. This factor could have a negative impact on efficiency in the short term if we consider that more than 30% of farmers are at the age of retirement (over 60 years old) and inexperienced persons could replace them. This also has major implications for government policies of turning over farms through land tenure reforms to new and possibly younger farmers with little to no experience. Efficiency loses would occur, as clearly seen with the experience variable in Figure 2.

The production system is another factor with a positive effect on efficiency. DPCS has been classified according to the type of beef animal (cow-calf, cow-yearling, and cow-steers) that is delivered into the markets. Basically the three systems use the same production technology, where the only difference is the male sale weight. Producers oriented to the cow-steer system were 6% and 8% more efficient than cow-calf and cow-yearling systems, respectively. However, the cow-steer system is implemented by only 12% of farmers. Farmers mainly use the cow-yearling system (84%) because they consider this system more flexible than the other two systems. Because of market conditions (milk

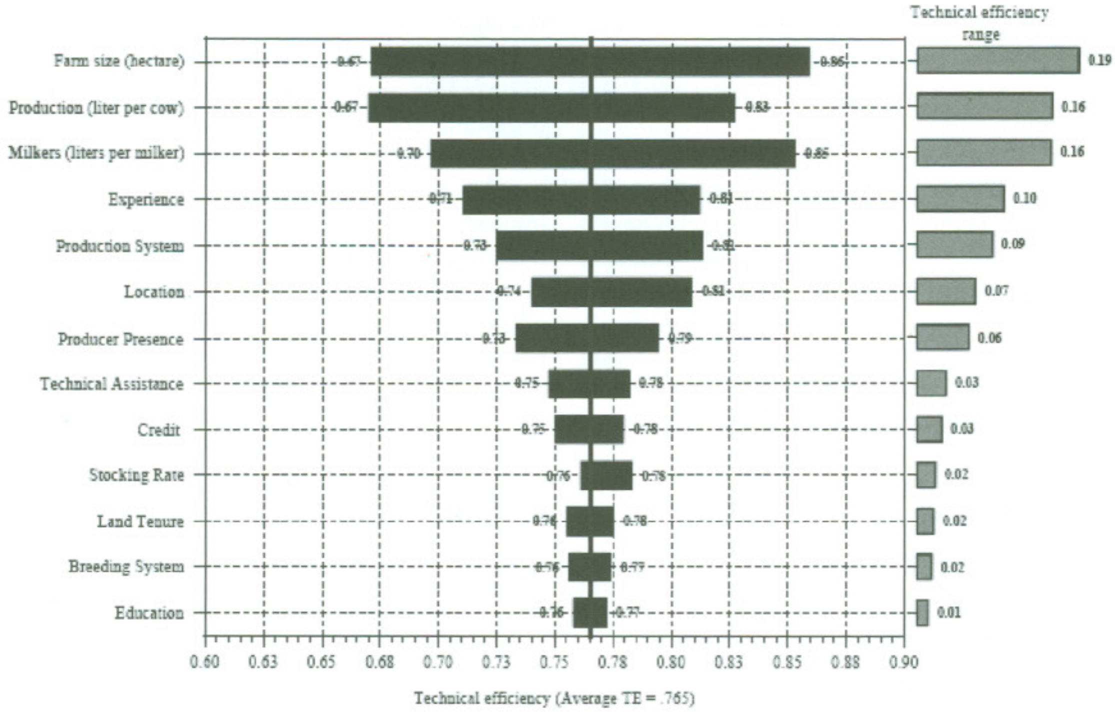

Figure 3. Ranking of Those Factors Impacting Technical Efficiency in the DPCS

and beef price) transitions between producing either more beef or milk will be easier and shorter using cow-yearling system.

Farms located in Rosario and Machiques de Perija counties (*Z31*) were at least 6% more efficient than the farms located in the other regions. The southern most section of the state (*Z1*), which is the agro-ecological area with more potential for agricultural production according to empirical evidence, was found to be the least efficient. A detail study addressing the specific characteristic of the farms in the different locations is necessary to explain this behavior.

Producers' presence on the farms has decreased in recent years because of the insecurity prevalent in the countryside. A policy oriented to promoting the presence of farmers in the work place will help to increase the efficiency of sector at least 8%, as seen in Figure 2.

The rest of the variables such as technical assistance, credit, stocking rate, land ownership, breeding practices, and education had considerably less impact on the technical efficiency. Assistance is one of those variables that potentially could be changed quickly through appropriate public polices, but it had minimal impact on the degree of technical efficiency. Yet expectation of achieving major efficiency gains with technical assistance must be put in perspective with the other factors impacting the efficiency. Alone some variable impacts may be small, but in combination more efficiency gains could possibly be achieved. For example, credit and technical assistance together produce a six-percentage point range. It is equally apparent that policies focusing on land tenure (i.e., ownership) and formal education have little impact on technical efficiency. Producer farming experience far outweighs any gains attributed to formal education.

For all agricultural sectors, achieving a high level of technical efficiency is essential for remaining competitive and being profitable. Likewise efficiency has direct implications for the public welfare since resources are used more effectively. Hence, public policies to assist agricultural systems such as the dual-purpose cattle system are logical for many of the Central and South American countries where the system is used extensively. Agricultural policies range from direct government substitutes such as credits to educational and technical assistance.

As illustrated in Figure 1, the level of technical efficiency in the dual-purpose cattle system has room for improvement, with nearly three-fourths of the farms having technical efficiency scores under .88. While it is encouraging that 25% of the farms were relatively efficient, effective public policies and private practices are particularly needed to address those farm characteristics generating much of the lower efficiency values (e.g., see the far right values in Figure 3). For the Venezuelan situation, significant gains can be expected when the policies focus on farm size, production practices, and labor productivity and less on factors such as land ownership. Policies addressing factors such as credit, producer presence, and technical assistance, while not ranked among the top factors, may be the easier to implement from a public policy and political standpoint. In contrast, the greatest range of technical efficiency is seen across farm sizes. Yet changing farm size through public policy may be totally contrary to the political system, and the efficiency gains may be far outweighed by the social costs from the implied land reform policies.

Conclusions

The objectives of this research were to estimate the production frontier, determine the level technical efficiency expressed as an index and create a standard for this system considering the total factor productivity concept, and define and evaluate the main factors influencing technical efficiency. The production frontier models revealed that the main factors that positively affected milk and beef production were labor, land, capital in machinery and cattle, veterinary medicine, and supplement feed.

A dual-purpose cattle system with an average value of efficiency of .765 is open to improvement. The simulation results show how the efficiency of DPCS can be improved from 2% to over 10% if public policies and managerial decisions create and respond to a secure environment in rural areas, review or reformulate and employ an effective credit program, encourage and use optimal labor and cow productivity levels, provide and employ technical assistance, and if farmers implement the cow-steer system. The results from this research give useful insight into how to address future studies to understand the effect of the relevant variables (i.e., production practices) and to evaluate the impact of specific farm policies.

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