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Technical efficiency and metatechnology ratios for dairy farms in three southern cone countries: a stochastic meta-frontier model

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Abstract This paper compares technical efficiency (TE) and metatechnology ratios (MTR) for dairy farms from Argentina, Chile and Uruguay using the meta-frontier (MF) approach. The estimated average MTRs for Argentina, Chile and Uruguay are 83.8, 79.6 and 91.4%, respectively, and these results are significantly different from each other. The TEs estimated with respect to the MF are 72.8, 65.8 and 73.4% for Argentina, Chile and Uruguay, respectively. The average TEs for Argentina and Uruguay are not significantly different from each other but are significantly higher than the value for Chile. The production frontiers for Argentina and Uruguay are relatively close to the MF, which suggests that these two countries might need to increase investments to promote local research to generate new technologies and/or search for technologies to adapt from more distant areas. By contrast, Chile could benefit from adaptive research, designed to make borrowed technology from Argentina and/or Uruguay applicable to local conditions, which could be a cost effective way to improve dairy farm performance.

Keywords Meta-frontiers · Technical efficiency · Metatechnology ratios · Southern cone countries · Dairy production

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1 Introduction

The dairy industry in many countries has been historically subject to considerable protection from a variety of governmental policies. However, milk producers worldwide are now facing growing competition from producers beyond their borders. In this rapidly emerging globalized environment, domestic producers must be prepared to make the best use of existing technologies and also to innovate and adopt new practices to remain competitive (Blayney and Gehlhar 2005).

In order to evaluate the competitiveness of a given firm it is necessary to have data for peers that allow one to compare relative performance. Recognizing the need for such data, the dairy branch of the International Farm Comparison Network (IFCN) was founded in 1997 and at present includes detailed cost and return information for 78 countries and 134 typical dairy farms (Hemme 2008). The information generated by the IFCN has the advantage of having global coverage including data from a large number of countries over a span of several years. However, an important limitation is the fact that it relies on "typical" farm data for just a few dairy operations for each country in each year.

In this paper, we take advantage of rarely available panel data sets for three Southern Cone countries, Argentina, Chile and Uruguay, which makes it possible to address several issues concerning dairy farm productivity. As has become well established in the literature, productivity growth can be decomposed into technical efficiency change (TEC), technological change (TC) and scale or size efficiency change (SEC) (Coelli et al. 2005). This decomposition is important because TEC can be interpreted as a relative measure of managerial ability given technology, while TC leads to increases in productivity that arise from the adoption of new production practices and SEC relates to changes in unit costs associated with the growth in the size of the firm. Consequently, gains in TEC are derived from improvements in managerial ability, which in turn are related to a host of variables including experience and education. By contrast, the driving force behind TC is investments in research and technology whereas SEC is determined by the ability of the firm to invest and procure new resources in order to expand its size.

Focusing on the dairy industry in Argentina, Chile and Uruguay is of interest given the relative importance and dynamism of this sector of the economy in these three neighboring countries. In the Argentinean case, the rate of growth of the milk productive sector has been erratic. Rapid growth was experienced between 1990 and 1999 with total production rising from 6,093 to 10,328 million liters. Subsequently, milk production dropped primarily because crop farming became significantly more profitable than dairy production. This situation led many dairy farmers to reduce grain and silage feeding and to return to a pasture-based system. As a result, Argentina experienced a sharp reduction in total milk production between 1999 and 2003, going from 10,328 to 7,951 million liters (SAGPYA-Argentina 2008). More recently, rapid growth has returned and total milk output reached 10,161 million liters in 2006 and over the past 2 years, production has stabilized around the 9,500 million liter mark (SAGPYA-Argentina 2009).

In Uruguay, the dairy production sector grew at an annual average rate of 4.4% between 1999/2000 and 2005/2006, reaching a total level of milk output equal to 1,620 million liters in 2005/2006 followed by a small reduction to 1,576 million liters in 2006/2007. On average, during the period 1999/2000 to 2003/2004 the export of dairy products generated around US $130 million in revenues per year. These figures imply an opening of the Uruguayan dairy sector to international trade and that farmers have been able to benefit from foreign markets. However, this scenario has evolved in tandem with a steady decline in the number of farms from around 6,700 in 1990/1991 to approximately 4,600 in 2006/2007 (MGAP-Uruguay 2009).

In Chile, the dairy production sector during the past 10 years grew at an annual average rate of 3%, reaching a total level of milk output equal to 1,970 million liters in 2008. Over the past several years, Chile has been adopting a wide range of economic reforms in an attempt to consolidate a modern free market system that is open to international trade. In this context, the commercial agreements signed by Chile have imposed a new scenario on all economic agents within the country. Increasing competition from imported products presents special challenges to traditional agricultural areas such as southern Chile, where dairy and wheat production are significant components of the farm economy (ODEPA-Chile 2009).

In the current environment of growing market liberalization and major macroeconomic challenges in many countries, productivity growth is an important mechanism to promote economic prosperity in general and in the agricultural sector in particular (Pinstrup-Andersen 2002; Ruttan 2002). The analysis of sources of productivity growth over time, and productivity differences among countries and regions have been important subjects of formal analysis in growth theory and development economics for many years. A few decades ago, Hayami and Ruttan (1970) argued that the effect of productivity growth in the agricultural sector is important if agricultural output is to rise at a rate sufficient to meet the growing demand for food and raw materials stemming from industrialization and urbanization. Furthermore, rapid rates of income and population growth are expected to double the demand for agricultural products over the next 50 years. Hence, substantial gains in productivity will be needed to keep up with this increase in demand (Ruttan 2002).

Capalbo et al. (1990) explain that productivity studies can be done at different levels, e.g., firm, sector, region or country. Several studies have estimated agricultural productivity growth among countries using aggregate data (Capalbo et al. 1990; Fulginiti and Perrin 1998; Coelli and Rao 2005). Country level studies are useful to compare and contrast macro trends, but are not helpful in formulating policies at the micro level. For instance, Bernard and Jones (1996) stress the point that productivity analyses based on aggregate country data cannot distinguish the behavior of specific sectors of the economy.

A few studies have used farm level data from different groups to compare technical efficiency (TE) measures across them using separate production frontier models for each group. For instance, Battese et al. (1993) estimated TE for wheat farms in selected districts of Pakistan. Their estimations were based on different stochastic production frontiers (SPF) for each district without testing if all districts used the same technology. Brümmer et al. (2002) estimated dairy farm TE for three European countries using separate stochastic distance functions to estimate country specific TE and then introduced intercept dummies in pooled data models to capture the country effect. Although the latter study is an improvement over the Battese, Malik and Broca paper, it still restricts any technology differences to a simple intercept effect. A major shortcoming of the two papers just cited is the lack of formal statistical tests to determine if technologies differ or not across regions. However, if different groups of farmers are indeed using the same technology, then TE should be measured with respect to a common frontier instead of relying on separate frontiers for each group. This is the motivation of the metafrontier (MF) approach introduced by Battese and Rao (2002), refined by Battese et al. (2004) and then by O'Donnell et al. (2008). Chen and Song (2008) appear to be the only authors that have published using the Battese et al. (2004) procedure for agriculture and their paper relies on regional level data for China.

The MF methodology is the foundation for the productivity analysis presented in this paper. The specific objective is to analyze TE and metatechnology ratios (MTR) for samples of dairy farms from Argentina, Chile and Uruguay. The specific objectives are to test explicitly the null hypothesis that these groups of farms share the same technology and to assess the effect of measuring and comparing TE and MTRs based on the MF approach versus separate country frontiers. This type of work is of particular relevance in Chile given ongoing policy efforts to implement technology innovation consortia designed to coordinate efforts from various economic agents in order to improve the competitiveness of strategic agricultural subsectors including dairy production (Consorcio Lechero 2009). Within this initiative, there is growing interest in establishing a bench marking system to compare the relative performance of dairy farms. Therefore, the present analysis makes a contribution to this effort, not only within Chile but also in two important neighboring countries. Argentina is crucial given that it shares a long border with Chile where significant improvements have taken place to facilitate cross border traffic. Moreover, Argentina is a major agricultural producer and has traditionally enjoyed cost advantages making producers in this country an important frame of reference for productivity comparisons in the Southern Cone (Hemme 2008).

The rest of this paper is divided into five sections. Section 2 presents an overview of the MF approach. Section 3 describes the data used and gives details on the empirical models followed by a discussion of the results. The paper ends with a summary of the main findings and some concluding comments.

2 Methodological framework

Hayami (1969), and Hayami and Ruttan (1970, 1971) introduced the concept of a meta-production function almost four decades ago. According to Hayami and Ruttan (1971, p 82), "the meta-production function can be regarded as the envelope of commonly conceived neoclassical production functions" assuming that all producers in different groups (e.g., countries, regions) have, potentially, access to the same technology. Following the seminal work of Hayami and Ruttan (1970), Mundlak and Hellinghausen (1982) and Lau and Yotopoulos (1989) employed the approach to compare agricultural productivity across countries.

The stochastic MF introduced by Battese and Rao (2002) is an extension of the meta-production function model. These authors argue that the MF model is an envelope of individual stochastic frontiers for different groups and is defined by the observations in all groups in a manner consistent with the well established frontier model. However, the original Battese and Rao procedure does not guarantee that the proposed MF production function is a true envelope of the estimated individual production frontiers for the different groups, a shortcoming that is addressed by Battese et al. (2004) and O'Donnell et al. (2008).

Suppose that separate stochastic production frontier (SPF) models are defined for specific groups of firms in a given industry. If for the j-th group there is data for N_j firms then the stochastic frontier model can be written as (Battese et al. 2004; O'Donnell et al. 2008):

$$y_{it} = f\left(x_{1it}, x_{2it}, \ldots, x_{Kit}; \beta^j\right) e^{v_{it}^j - u_{it}^j}, \tag{1}$$

where y_{it} is the output for the i-th firm in the j-th group for time period t; x_{kit} is the k-th input ($k = 1, 2, \ldots, K$) for the i-th firm in the j-th group for time period t; v_{it}^j is a random error assumed to follow a normal distribution with mean zero and constant variance ($v_i^j \sim iid\, N(0, \sigma_{vj}^2)$); and u_{it}^j is a non-negative unobservable random error associated with the technical inefficiency of the i-th firm. For simplicity, the superscript j is omitted on the input and output variables.

If it is assumed that the exponent of the production frontier is linear in the parameter vector β^j, then the technology can be represented by a suitable functional form (e.g., Cobb-Douglas (CD) or translog (TL)) and the model can be written as (Battese et al. 2004):

$$y_{it} = f\left(x_{1it}, x_{2it}, \ldots, x_{Kit}; \beta^j\right) e^{v_{it}^j - u_{it}^j} \equiv e^{\mathrm{x}_{it}' \beta^j + v_{it}^j - u_{it}^j}, \tag{2}$$

where x_{it} is a column vector of inputs for the i-th firm in the t-th period associated with the j-th group. Input and output data for firms in the j-th group can be used to obtain maximum-likelihood (ML) estimates of the unknown parameters of the frontier defined in Eq. 2. TE for the i-th firm in the t-th period associated with the j-th group with respect to its own frontier can then be computed, following Battese and Coelli (1992), as:

$$TE_{it}^j = \frac{y_{it}}{e^{\mathrm{x}_{it}'\beta^j + v_{it}^j}} = e^{-u_{it}^j}. \tag{3}$$

After estimating the frontiers in Eq. 2 for each group separately, it is necessary to verify if the various groups share the same technology. This can be done with a likelihood ratio test (LR), where $L(H_0)$ is the value of the log-likelihood function for the stochastic frontier estimated by pooling the data for all groups and $L(H_A)$ is the sum of the values of the log-likelihood functions from the individual production frontiers.[1] The degrees of freedom for the Chi-square statistic is the difference between the number of parameters estimated under H_A and H_0. If the null hypothesis that the stochastic frontier for the pooled data is rejected in favor of the individual frontiers (H_A), then the data should not be pooled and in such case the MF is the appropriate framework to estimate and compare TE across groups (Battese et al. 2004).

The MF model is defined by Battese et al. (2004) as a deterministic parametric frontier of specified functional form (e.g., CD or TL) such that the predicted value for the MF is larger than or equal to the predicted value from the stochastic frontier for all firms, groups, and time periods. Moreover, the MF is assumed to be a smooth function and not a segmented envelope of the stochastic frontier functions for the different groups (Battese et al. 2004). Thus, the deterministic MF model for all firms in all groups can be expressed as follows:

$$y_{it}^* = f(x_{1it}, x_{2it}, \ldots, x_{Kit}; \beta^*) \equiv e^{x_{it}'\beta^*}, \tag{4}$$

where y_{it}^* and β^*denote MF output and the vector of parameters for the MF model, respectively, provided the following condition holds for all j-groups ($j = 1, 2, \ldots, J$):

$$x_{it}'\beta^* \geq x_{it}'\beta^j. \tag{5}$$

According to Battese et al. (2004), the parameters of the MF model can be obtained using two alternative criteria: (1) by minimizing the sum of the absolute deviations (MAD) of the distance between the MF and the j-th group frontier evaluated at the observed input vector for a firm in the j-th group; and/or (2) by minimizing the sum of the squares of the deviations of the values on the MF from those of the group specific stochastic frontiers at the observed input levels. These authors reported similar results for the two approaches and argue that the principle of parsimony favors the MAD approach and for these reasons it is the option implemented below.

Therefore, to estimate the MF, the objective function to be minimized is the sum of the absolute deviations subject to Eq. 5. The respective linear programming (LP) problem to be solved can be written as:

$$\begin{aligned} \underset{\beta^*}{\text{Min}} \sum_{i=1}^{N}\sum_{t=1}^{T} \Big[&\ln f(x_{1it}, x_{2it}, \ldots, x_{Kit}; \beta^*) \\ &- \ln f\left(x_{1it}, x_{2it}, \ldots, x_{Kit}; \hat{\beta}^j\right)\Big] \\ \text{s.t. } \ln f(x_{1it}, x_{2it}, \ldots, x_{Kit}; \beta^*) &\geq \ln f\left(x_{1it}, x_{2it}, \ldots, x_{Kit}; \hat{\beta}^j\right). \end{aligned} \tag{6}$$

This problem is solved using the pooled dataset and thus includes all observations for all groups. Since $\hat{\beta}^j$, the vector of estimated coefficients for the stochastic frontier for each j-th group, and the input vectors are assumed to be fixed, the following equivalent form of the LP problem in Eq. 6 can be specified if the function $f(x_{1it}, x_{2it}, \ldots, x_{Kit}; \beta^*)$ is log-linear in the parameters (as assumed in the empirical application of this research):

$$\begin{aligned} &\underset{\beta^*}{\text{Min}}\ \bar{\mathbf{x}}'\beta^* \\ &\text{s.t. } x_{it}'\beta^* \geq x_{it}'\beta^j, \end{aligned} \tag{7}$$

where $\bar{\mathbf{x}}$ is the arithmetic average of the $\mathbf{x}_{it}$ vectors over all i firms in all t periods for the j-th group (Battese et al. 2004).

Once the LP problem in Eq. 7 is solved, TE with respect to the MF (TE^*) can be estimated for each observation in the data set. The difference between TE^* (TE with respect to the MF) and TE^j (TE with respect to a group/country frontier from Eq. 3) for a given firm is due to a gap between the individual group frontier and the meta-frontier. This gap, called the Technology Gap Ratio (TGR^j) by Battese et al. (2004), and Metatechnology Ratio (MTR^j) by O'Donnell et al. (2008), is defined as the difference (or gap) in the technology available to a given (j-th) group relative to the technology available to all groups/countries under consideration taken together. In this paper we use the O'Donnell, Rao and Battese concept (MTR), which indicates that "increases in the technology gap ratio imply a decrease in the gap between the group frontier and the meta-frontier" (O'Donnell et al. 2008, p. 236).

The mathematical expression for TE_{it}^*, which is computed from the MF, can be expressed as:

$$T\hat{E}_{it}^* = T\hat{E}_{it}^j \times M\hat{T}R_{it}^j, \tag{8}$$

where $T\hat{E}_{it}^j$ is the TE of the i-th firm in the t-th period with respect to the j-th group frontier, defined by Eq. 3. Thus, $T\hat{E}_{it}^*$ is equal to the TE relative to the stochastic frontier for a given group $\left(T\hat{E}_{it}^j\right)$ times the gap between the group frontier and the MF $\left(M\hat{T}R_{it}^j\right)$.

The expression for $M\hat{T}R_{it}^j$ proposed by Battese and Rao (2002), Battese et al. (2004) and O'Donnell et al. (2008) is:

$$M\hat{T}R_{it}^j = \frac{e^{x_{it}'\beta^j}}{e^{x_{it}'\beta^*}} = \frac{T\hat{E}_{it}^*}{T\hat{E}_{it}^j}, \tag{9}$$

[1] The LR statistic is given by $\lambda = 2\,[\ln\{L(H_A)\} - \ln\{L(H_0)\}]$, where $L(H_A)$ and $L(H_0)$ are the values of the likelihood function under the alternative and null hypotheses. The value of λ has a Chi-square distribution with the number of degrees of freedom equal to the number of restrictions imposed.

where $e^{x'_{it}\beta^j}$ is the deterministic component of Eq. 2 and $e^{x'_{it}\beta^*}$ is defined in Eq. 4. An alternative expression for $T\hat{E}^*_{it}$ is given by:

$$TE^*_{it} = \frac{y_{it}}{e^{x'_{it}\beta^* + v^j_{it}}}. \tag{10}$$

The denominator in (10) is the frontier output adjusted by the corresponding random error.

3 Data and empirical models

The Argentinean data come from a sample of farms located in the Abasto Sur area of Buenos Aires province. The data were collected over three agricultural years (1997/1998, 1999/2000 and 2001/2002) and includes 46 farms with a total of 82 observations. The data for the Chilean sample come from 48 small dairy farms located in southern Chile for the periods 1996/1997, 1998/1999, 1999/2000, 2000/2001 and 2001/2002 with a total of 92 observations. The Uruguayan data come from surveys of dairy farms over four agricultural years: 1999/2000, 2000/2001, 2001/2002 and 2002/2003, for 70 farms with a total of 147 observations. Thus, the data for all three countries are unbalanced panels. All variables expressed in monetary values were available in nominal dollars for each period and country. The nominal dollars were converted to real dollars by multiplying the latter by the USA CPI divided by the CPI of each country for the relevant time period. All figures are then converted to real dollars using July 2004–June 2005 as the base period. A brief description of the variables is included in Table 1.

The one-sided error term, u_{it}, incorporated in the SPF models shown in Eqs. 1 and 2 can have different specifications, and the non-negative truncation of a normal distribution and the half-normal distribution are the most commonly used. Coelli et al. (2005) suggest that the choice of a more general distribution, such as the truncated-normal distribution, is usually preferable. However, this is ultimately an empirical matter; thus, the truncated-normal distribution is tested against the half-normal. An additional consideration regarding the one sided error term is to test if TE increases, remains constant or decreases over time, an issue that is also examined below. All parameters for the SPF models are estimated using FRONTIER 4.1 (Coelli 1996) while those for the MF (Eq. 7) are estimated using the Shazam econometric software.

The first step is the estimation of the individual country-specific SPF models, where the dependent variable is the natural logarithm of annual per farm milk output (y) measured in liters (L). The production frontier model for the CD technology representation can be written as:

$$y_{it} = \beta^j_0 + \beta^j_{CO}\mathrm{CO}_{it} + \beta^j_{LB}\mathrm{LB}_{it} + \beta^j_{FD}\mathrm{FD}_{it} + \beta^j_{VE}\mathrm{VE}_{it} + \beta^j_t t + v^j_{it} - u^j_{it}, \tag{11}$$

where the subscripts it refer to the i-th farm in time period t, and superscript j denotes the country. The explanatory variables, also expressed in natural logarithms, are the following: CO is the average number of dairy cows; LB is labor measured in worker-equivalents; FD is purchased feed, including concentrate feed, hay and minerals, plus all costs associated with the on-farm production of hay, silage and pastures, measured in constant US dollars (the base year is July 2004–June 2005); and VE is total expenditures in veterinary care and medicine also measured in US dollars. The definition of t, a smooth time trend to capture TC (technological change), varies with each data set as follows: for Argentina t is $1 = 1997/1998$, $3 = 1999/2000$, and $5 = 2001/2002$; for Chile it is $1 = 1996/1997$, $3 = 1998/1999$, $4 = 1999/2000$, $5 = 2000/2001$, and $6 = 2001/2002$; for Uruguay it is $1 = 1999/2000$, $2 = 2000/2001$, $3 = 2001/2002$ and $4 = 2002/2003$. For the pooled data, t is $1 = 1996/1997$, $2 = 1997/1998$, $3 = 1998/1999$, $4 = 1999/2000$, $5 = 2000/2001$, $6 = 2001/2002$ and $7 = 2002/2003$. The random variables v_{it} and u_{it} are as defined in Eqs. 1 and 2, and the Greek letters represent unknown parameters to be estimated.

The translog (TL) specification uses the same dependent and explanatory variables detailed above, but includes the second-order interaction terms. Omitting the superscript j for simplicity, the TL frontier can be represented as:

$$y_{it} = \alpha_0 + \sum_{k=1}^{4}\beta_k x_{kit} + \frac{1}{2}\sum_{k=1}^{4}\sum_{l=1}^{4}\beta_{kl}x_{kit} \times x_{lit} + \sum_{k=1}^{4}\delta_k x_{kit} \times t + \lambda_1 t + \frac{1}{2}\lambda_{11}t^2 + v_{it} - u_{it}, \tag{12}$$

where the subscript k represents the k-th explanatory variable. All data for the TL model are expressed as deviations from their sample geometric means, which makes it possible to interpret the first-order parameters directly as partial production elasticities at the geometric mean of the data (Coelli et al. 2003).

Finally, the results from the preferred models are used to estimate the MF parameters by solving the LP problem of Eq. 7.

4 Empirical results and analysis

This section describes the results of the estimation of the individual country frontiers and associated TE measures. First, the SPF results and specification tests are analyzed for both the individual countries and for the pooled data. Second, TE measures are discussed for the three countries

Table 1 Descriptive statistics for dairy farm data for Argentina, Chile and Uruguay

Country/variable	Overall mean	Mean for period				
Argentina		1997/1998	1999/2000	2001/2002		
Milk (L year^{-1})	1,028,372	1,064,015	980,191	1,019,305		
	523,977	*521,096*	*575,399*	*501,568*		
Milk cows (number year^{-1})	160	151	159	174		
	72	*63*	*76*	*80*		
Labor (worker-equivalent)	4.6	5.0	4.3	4.2		
	1.8	*2.0*	*1.5*	*1.6*		
Feed expenses (\$ year^{-1})[a]	110,387	145,721	108,919	64,006		
	67,724	*69,786*	*63,874*	*31,406*		
Veterinary expenses (\$ year^{-1})[a]	11,634	14,028	12,900	7,389		
	7,364	*7,938*	*7,824*	*3,593*		
Number of farms	82	35	21	26		
Chile		1996/1997	1998/1999	1999/2000	2000/2001	2001/2002
Milk (L year^{-1})	55,010	33,016	45,000	56,810	84,285	95,469
	47,929	*20,677*	*39,759*	*44,098*	*57,600*	*69,135*
Milk cows (number year^{-1})	25	21	24	27	29	31
	15	*10*	*14*	*20*	*13*	*17*
Labor (worker-equivalent)	3.3	3.9	3.6	3.2	2.2	2.5
	2.3	*1.4*	*3.2*	*1.9*	*0.4*	*1.2*
Feed expenses (\$ year^{-1})[a]	3,214	2,063	1,837	2,919	3,806	9,388
	3,896	*1,174*	*1,772*	*3,167*	*2,362*	*7,214*
Veterinary expenses (\$ year^{-1})[a]	316	287	187	337	510	544
	299	*180*	*206*	*224*	*416*	*471*
Number of farms	92	20	33	18	10	11
Uruguay		1999/2000	2000/2001	2001/2002	2002/2003	
Milk (L year^{-1})	848,321	875,259	739,653	914,308	892,313	
	655,832	*537,802*	*615,381*	*699,623*	*833,278*	
Milk cows (number year^{-1})	213	206	188	233	235	
	153	*131*	*134*	*169*	*192*	
Labor (worker-equivalent)	5.1	5.3	4.8	5.3	5.3	
	2.6	*2.3*	*2.6*	*2.6*	*3.1*	
Feed expenses (\$ year^{-1})[a]	63,588	88,892	57,634	55,849	42,771	
	56,189	*63,690*	*52,515*	*51,409*	*41,932*	
Veterinary expenses (\$ year^{-1})[a]	15,542	19,606	13,801	16,058	10,944	
	11,447	*11,282*	*10,928*	*10,905*	*11,641*	
Number of farms	147	42	43	37	25	

Standard deviations in italics

[a] US \$, the reference year is July 2004–June 2005

and then the TE and MTR measures with respect to the MF are examined.

4.1 Production frontier estimates and specification tests by country and for the pooled data

Table 2 includes estimates for the CD and TL specifications using the SPF approach for the three countries (Models AR-I and AR-II for Argentina, Models CH-I and CH-II for Chile, and Models UR-I and UR-II for Uruguay). The roman numerals I and II denote CD and TL, respectively. The estimates for the pooled data (Models PS-I and PS-II) are in Table 3. The various models are estimated in order to evaluate the impact of different assumptions on TE measures and to determine the most appropriate specifications for the data under analysis. Model selection is made

Table 2 Parameter estimates for Cobb-Douglas (CD) and translog (TL) production frontiers for Argentinean (AR), Chilean (CH) and Uruguayan (UR) dairy farms

	Model AR-I (CD)		Model AR-II (TL)		Model CH-I (CD)		Model CH-II (TL)		Model UR-I (CD)		Model UR-II (TL)	
Const.	8.008***	*0.368*	0.012	*0.034*	7.366***	*0.192*	0.173**	*0.081*	5.451***	*0.472*	0.268***	*0.048*
CO	0.917***	*0.048*	0.774***	*0.055*	0.893***	*0.087*	0.488***	*0.096*	0.535***	*0.082*	0.554***	*0.084*
LB	0.193***	*0.051*	0.193***	*0.047*	0.174**	*0.099*	0.195*	*0.150*	0.058	*0.089*	0.103	*0.093*
FD	0.087***	*0.034*	0.115***	*0.042*	0.037***	*0.014*	0.289***	*0.055*	0.345***	*0.057*	0.232***	*0.059*
VE	0.003	*0.014*	0.149***	*0.045*	0.014	*0.014*	0.128***	*0.042*	0.146***	*0.050*	0.179***	*0.052*
t	−0.017	*0.011*	0.009	*0.012*	0.097***	*0.025*	0.026	*0.026*	0.086***	*0.019*	0.069***	*0.022*
CO^2			0.116	*0.146*			0.031	*0.177*			−0.307	*0.226*
LB^2			0.144	*0.113*			0.176	*0.171*			0.017	*0.294*
FD^2			0.134**	*0.058*			0.015**	*0.007*			0.074	*0.085*
VE^2			0.003	*0.007*			0.005	*0.005*			−0.118**	*0.057*
t^2			0.037***	*0.008*			−0.057***	*0.017*			0.005	*0.021*
CO × LB			−0.334*	*0.201*			−0.362	*0.342*			0.364	*0.422*
CO × FD			−0.061	*0.088*			−0.031	*0.126*			0.076	*0.202*
CO × VE			−0.024	*0.123*			0.017	*0.100*			0.230	*0.218*
CO × t			−0.057	*0.039*			−0.014	*0.077*			0.103	*0.104*
LB × FD			−0.030	*0.095*			−0.056	*0.161*			−0.222	*0.253*
LB × VE			0.043	*0.138*			0.089	*0.145*			0.012	*0.231*
LB × t			0.033	*0.040*			−0.059	*0.092*			−0.157	*0.108*
LB × VE			−0.025	*0.082*			0.038	*0.057*			−0.103	*0.136*
FD × t			0.008	*0.026*			0.012	*0.040*			0.067	*0.054*
VE × t			0.073***	*0.023*			0.029	*0.039*			−0.054	*0.064*
FC	1.200		1.231		1.119		1.100		1.085		1.068	
LLF	49.454		67.193		−20.862		0.288		38.327		54.194	
σ^2	0.031***	*0.008*	0.036***	*0.011*	0.256***	*0.063*	0.092***	*0.028*	0.083***	*0.021*	0.090***	*0.028*
γ	0.597***	*0.142*	0.860***	*0.064*	0.810***	*0.066*	0.512***	*0.201*	0.749***	*0.090*	0.844***	*0.073*

Argentina has 46 farms with 82 observations, Chile has 48 farms with 92 observations, Uruguay has 70 farms with 147 observations

Standard errors in italic

CO number of cows, *LB* labor, *FD* feed cost, *VE* veterinary expenses, *t* time, *FC* function coefficient, *LLF* log-likelihood function

*** 1% level of significance; ** 5% level of significance; * 10% level of significance

on the basis of likelihood ratio tests which are summarized in Table 4. Most models exhibit positive and significant first-order parameters (the exceptions are detailed in each case), fulfilling the monotonicity condition as expected for a well behaved production function. Table 4 also shows a set of pair-wise log likelihood ratio tests to compare across the CD and TL models and the results show that the TL is consistently the preferred functional form, and thus the analysis below is based on the latter.

The Argentinean SPF model exhibits highly significant first-order parameter estimates, with the exception of t (time). The parameter for t^2 (time squared) is positive and significant, indicating that the rate of TC increases at an increasing rate over time. The only significant parameter for the interaction terms is for t times VE (veterinary expenses) and its positive value suggests that TC has been veterinary expenses-saving over the period, thus TC is non-neutral. The function coefficient for the TL at the geometric mean is 1.231 revealing increasing returns to size (RTS) and that, on average, farms in the Argentinean sample are operating at a sub-optimal size. Moreover, the coefficient for CO (cows) is the largest among the partial elasticities, which implies that a percent change in the number of cows has a larger influence on milk production than the same relative change on any other input. This result is consistent with several other dairy studies including Kumbhakar et al. (1991), Heshmati and Kumbhakar (1994), Ahmad and Bravo-Ureta (1996), Cuesta (2000) and Lawson et al. (2004a, b).

Most first order parameters for the TL model for Chile are highly significant, with the exception of LB (labor) and t. Much of what has been said for Argentina is also valid for Chile, but one difference is that the parameter for t^2 is negative and significant, indicating that the rate of TC decreases at a decreasing rate over time. None of the parameters for the interaction between t and the other inputs is significant, which suggests neutral TC. Again, the

Table 3 Parameter estimates for production frontier models and the meta-frontier (MF) for the pooled sample (PS)

Variables/models	Model PS-I (CD)		Model PS-II (TL)		Model-MF (Meta-frontier)
Constant	6.355***	*0.189*	0.180***	*0.030*	0.325
Cows (CO)	0.912***	*0.042*	0.642***	*0.047*	0.586
Labor (LB)	−0.016	*0.038*	0.150***	*0.048*	0.216
Feed (FD)	0.239***	*0.023*	0.199***	*0.029*	0.191
Veterinary expenses (VE)	0.027***	*0.010*	0.103***	*0.024*	0.122
Time (t)	−0.028**	*0.012*	0.037***	*0.009*	0.061
CO^2			0.034	*0.103*	0.034
LB^2			0.149*	*0.087*	0.149
FD^2			0.014***	*0.003*	0.013
VE^2			0.004	*0.003*	0.010
t^2			−0.004	*0.005*	0.004
CO × LB			−0.086	*0.169*	0.111
CO × FD			−0.063	*0.062*	−0.071
CO × VE			−0.020	*0.065*	−0.082
CO × t			−0.028	*0.032*	−0.081
LB × FD			−0.079	*0.070*	−0.131
LB × VE			0.034	*0.069*	−0.085
LB × t			0.041	*0.033*	0.044
LB × VE			0.027	*0.025*	0.073
FD × t			−0.007	*0.016*	0.009
VE × t			0.045***	*0.015*	0.046
Function coefficient	1.163		1.094		1.115
Log-likelihood function	−55.173		49.881		
σ^2	0.290***	*0.034*	0.092***	*0.014*	
γ	0.872***	*0.018*	0.706***	*0.061*	
η[a]	0.160***	*0.027*			

Pooled sample and MF analysis include 164 farms with 331 observations

Standard errors in italic

*** 1% level of significance, ** 5% level of significance, * 10% level of significance

[a] This parameter is available only when estimated TE is time-variant

function coefficient (equal to 1.100 for the TL model) indicates the presence of increasing RTS. This result is consistent with the fact the dairy farms in the Chilean sample are relatively small (Table 1).

The estimates for the TL SPF model for Uruguay, also shown in Table 2, exhibit highly significant first-order parameters with the exception of LB. The parameter for t^2 is non-significant, indicating that the rate of TC does not change over time. As in the Chilean case, none of the parameters for the interaction between t and other inputs is significant, suggesting neutral TC. The function coefficient again indicates the presence of increasing RTS (equal to 1.068 for the TL).

Table 3 shows the parameter estimates for the CD and TL models for the pooled sample and the linear programming estimates for the MF. Again, the following analysis is based on the TL specification. The econometric model exhibits highly significant first-order parameter estimates. The parameter for t^2 is not significant, and none of the parameters for the interaction between t and the other inputs is significant. The function coefficient for the pooled TL stochastic model is 1.094, falling between those of the individual country SPF models (Table 2). Finally, Table 3 includes the parameters for the MF model (LP) and they are similar with those obtained in both the individual country and pooled models.

Table 4 presents results associated with various tests designed to evaluate first the general specifications of the models and then alternative hypotheses concerning the inefficiency component. The first test focuses on the statistical significance of the γ parameter (H_0: $\gamma = 0$), which compares the stochastic frontier model versus the average production function. The closer γ is to 1, the more significant the presence of technical inefficiency (Battese and Coelli 1992). The γ parameters shown in Tables 2 and 3 range from 0.512 for Model CH-II to 0.872 for Model

Table 4 Specifications test for all production frontier models

Null hypotheses H_0	χ^2 statistic[a]	χ^2 0.95 value (*df*)	Decision	Choice
Single country models				
Argentina (AR)				
Model AR-I				
$\gamma = 0$	6.93	3.84 (1)	Reject H_0	Stochastic
$\mu = 0$	0.15	3.84 (1)	Do not reject H_0	Half-normal
$\eta = 0$	0.06	3.84 (1)	Do not reject H_0	Time-invariant
Model AR-II				
$\gamma = 0$	19.40	3.84 (1)	Reject H_0	Stochastic
$\mu = 0$	2.20	3.84 (1)	Do not reject H_0	Half-normal
$\eta = 0$	1.65	3.84 (1)	Do not reject H_0	Time-invariant
Model AR-I vs. Model AR-II[b]	35.48	25.00 (15)	Reject H_0	TL
Chile (CH)				
Model CH-I				
$\gamma = 0$	20.44	3.84 (1)	Reject H_0	Stochastic
$\mu = 0$	0.13	3.84 (1)	Do not reject H_0	Half-normal
$\eta = 0$	1.44	3.84 (1)	Do not reject H_0	Time-invariant
Model CH-II				
$\gamma = 0$	2.90	3.84 (1)	Do not reject H_0	Deterministic
$\mu = 0$	0.02	3.84 (1)	Do not reject H_0	Half-normal
$\eta = 0$	0.13	3.84 (1)	Do not reject H_0	Time-invariant
Model CH-I vs. Model CH-II[b]	40.86	25.00 (15)	Reject H_0	TL
Uruguay (UR)				
Model UR-I				
$\gamma = 0$	17.31	3.84 (1)	Reject H_0	Stochastic
$\mu = 0$	0.02	3.84 (1)	Do not reject H_0	Half-normal
$\eta = 0$	3.01	3.84 (1)	Do not reject H_0	Time-invariant
Model UR-II				
$\gamma = 0$	21.05	3.84 (1)	Reject H_0	Stochastic
$\mu = 0$	0.55	3.84 (1)	Do not reject H_0	Half-normal
$\eta = 0$	0.82	3.84 (1)	Do not reject H_0	Time-invariant
Model UR-I vs. Model UR-II[b]	31.74	25.00 (15)	Reject H_0	TL
Pooled sample (PS) models				
Model PS-I				
$\gamma = 0$	140.85	7.82 (3)	Reject H_0	Stochastic
$\mu = 0$	39.03	3.84 (1)	Reject H_0	Trunc.-normal
$\eta = 0$	11.80	3.84 (1)	Reject H_0	Time-variant
Model PS-II				
$\gamma = 0$	37.87	3.84 (1)	Reject H_0	Stochastic
$\mu = 0$	1.08	3.84 (1)	Do not reject H_0	Half-normal
$\eta = 0$	0.24	3.84 (1)	Do not reject H_0	Time-invariant
Model PS-I vs. Model PS-II[b]	210.11	22.36 (13)	Reject H_0	TL
Pooled sample versus individual country frontiers				
Pooled sample vs. sum of individual log-likelihood	143.59	67.51 (50)	Reject H_0	Meta-Frontier

[a] This statistic has a mixed c^2 distribution

[b] Read as Restricted model versus Unrestricted model

PS-II. The statistical tests reflect that all models are indeed stochastic frontiers at the 5% level of significance or better, with the exception of the Chilean case, for which γ is significant at the 10% level or better (Table 4). In sum, for all models the stochastic frontier dominates the average production function.

The second step is to test the null hypothesis that the one-sided distribution is half-normal (H_0: $\mu = 0$), which is accepted for all models (Table 4). This result indicates that in most cases the half-normal distribution is more compatible with the data under analysis than the truncated-normal, a finding that is consistent with several dairy farm studies including Kumbhakar and Heshmati (1995) and Ahmad and Bravo-Ureta (1996). In addition, Coelli et al. (2005) argue that choosing different distributional assumptions can give rise to different predictions of TE, but when the rank correlations of the TEs from the different models is robust, the principle of parsimony favors the simpler half-normal and exponential distributions.

The third step is to test the null hypothesis that TE is time-invariant (H_0: $\eta = 0$) and the results reveal that all TE effects are indeed time-invariant. Finally, and of major importance to the subsequent analysis, Table 4 shows the result of the LR test to examine the null hypothesis that the three countries share the same technology. If the three countries were to share the same production frontier (i.e., no significant difference between the single country frontiers), then there would be no reason for estimating the pooled MF production model. The value of the LR statistic is 143.59 (50 *df*), which implies that the null hypothesis is strongly rejected. Therefore, this result suggests that the stochastic frontiers for dairy farms in Argentina, Chile and Uruguay are not the same and that any efficiency comparison across these three samples should be undertaken with respect to the LP MF instead of the pooled stochastic frontier. It appears that this approach has been applied only in three published studies and, in all cases, the MF has been found to be the valid framework to compare the groups under analysis (Battese et al. 2004; Chen and Song 2008; O'Donnell et al. 2008).

4.2 Metatechnology ratio (MTR) and technical efficiency (TE) analysis with the meta-frontier (MF)

The values of the MTR and the TE measures for the SPF and with respect to the MF are summarized in Table 5. In general, a higher (lower) MTR value implies a smaller (larger) technology gap between the individual frontier and the MF. A value of 100% is equivalent to a point where the individual country frontier coincides with the MF. The average estimated MTR for the Argentinean case is 83.8%, ranging from a minimum of 58.3% to a maximum of 100.0%; the average estimated MTR for the Chilean case is 79.6%, and ranges from a minimum of 43.2% to a maximum of 100.0%; and the average for the Uruguayan case is 91.4%, and goes from a low of 53.5% to a high of 100.0%. The average MTRs for the three countries are statistically different from each other.[2] Thus, the highest average MTR is for Uruguay (91.4%), which means that these farmers are closer to the MF than their Argentinean and Chilean counterparts. Conversely, the lowest average MTR is for Chile (79.6%) and this may be related to the fact that the Chilean farms are smaller and have less access to technology while the Argentinean MTR exhibits an intermediate value (83.8%). Battese et al. (2004) found similar average MTRs in their research on Indonesian garment firms.

Table 5 Metatechnology ratio (MTR) and technical efficiency (TE) for selected production frontier models

	Average	SD	Minimum	Maximum
Metatechnology ratio (MTR)				
Argentina	83.8	10.7	58.3	100.0
Chile	79.6	12.0	43.2	100.0
Uruguay	91.4	7.5	53.5	100.0
Technical efficiency (TE)				
Argentina				
TL model	87.0	7.6	69.1	97.9
MF[a]	72.8	11.3	42.2	91.6
Pooled[b]	85.0	6.0	68.4	93.1
Chile				
TL model	84.9	6.7	64.4	94.8
MF[a]	65.8	9.9	42.1	85.5
Pooled[b]	81.2	11.0	51.3	96.2
Uruguay				
TL model	81.1	10.9	49.3	97.1
MF[a]	73.4	12.7	40.4	91.0
Pooled[b]	82.0	9.6	54.9	96.5
Pooled sample				
TL model	82.6	9.3	51.3	96.5

[a] MF: TE measured with respect to the meta-frontier (MF)

[b] TE calculated from the TL model

Producers benefit directly from gains in TE because such gains translate into improvements in incomes (Bravo-Ureta and Rieger 1991; Lawson et al. 2004b). The average TE measures calculated from the country specific SPF models compared with those from the MF are 87.0 and 72.8% for Argentina, 84.9 and 65.8% for Chile, and 81.1 and 73.4% for Uruguay (Table 5), and these differences are statistically significant. In addition, when average TEs are compared with respect to the MF, the averages for Argentina (72.8%) and Uruguay (73.4%) are equal and significantly higher than for Chile (65.8%). A comparison of the average TE across the three countries, calculated from the pooled stochastic frontier, indicates that there is

[2] Independent *t*-tests and one-way ANOVA are used to compare different figures. The former is used to compare means between two groups whereas the latter is applied when comparing more than two groups (Field 2005).

no significant difference (Argentina = 85.0%, Chile = 81.2%, Uruguay = 82.0%). This result lends additional support to the relevance of using the MF, i.e., a suitable technology of reference, to compare the performance across countries (or groups).

An important policy implication of efficiency analysis across countries is to ascertain the relevance of catching-up, i.e., of productivity gains attainable by increasing TE (Battese et al. 2004; O'Donnell et al. 2008). This is particularly important in the short run because TE is expected to be responsive to targeted training programs which in many countries can be implemented without new investments, with moderate planning and at a relatively low cost. The results of this research indicate that the opportunities for catching-up are relevant in all three countries being much higher for Chile than Argentina and Uruguay. In other words, the farms in the Chilean sample could improve their performance by borrowing the prevailing agricultural practices in the neighboring countries of Argentina and Uruguay. It is worthwhile noting that the Chilean government has established programs that finance technical visits to other countries with the intention of learning new farm practices and capturing technologies employed elsewhere (FIA-Chile 2009). These programs should stay focused on giving incentives to enable less efficient farmers to catch up with those that are closer to the frontier and who provide examples of best practice.

As mentioned by O'Donnell et al. (2008), farmers in different countries have different production opportunities, which are reflected in their input–output combinations. The observed heterogeneity in production technologies results from differences in a wide range of physical, social, economic and environmental conditions under which production takes place. Clearly, at least some and perhaps several of these conditions cannot be changed within a reasonable span of time and/or financial resources. However, the results of this paper suggest that some constraints facing farmers in a given location might be subject to improvement based on local research and/or by borrowing know-how from more advanced environments or producers.

Consequently, if the production frontier for farmers in a given country is far away from the MF then adaptive research, designed to make borrowed technology from neighboring regions applicable to local conditions, could be a sensible course of action to facilitate movement towards the MF. On the other hand, countries that are close to the MF might need to pursue a different research strategy which is likely to require additional investments in local research to develop new technologies and/or a search for technologies to adapt from more distant areas. The results of this study indicate that Argentina and Uruguay fall in this latter situation. By contrast, Chile could benefit from looking closely at the practices and technologies that prevail in Argentina and Uruguay as a strategy to improve dairy farm performance. In the case of dairy production, animal genetics together with feed and feeding practices are key areas that can have a major impact on productivity and that are suitable for both adaptive and original research (Smith et al. 2002; Anrique et al. 2004).

Table 6 Spearman rank correlation coefficients for technical efficiency (TE) measures for translog (TL) stochastic production frontier (SPF) and meta-frontier (MF) models

Country/model	TL	Meta-frontier
Argentina		
TL	1.00	
MF[a]	0.80	1.00
	CH-II	MF
Chile		
TL	1.00	
MF[a]	0.44	1.00
	UR-II	MF
Uruguay (UR)		
TL	1.00	
MF[a]	0.85	1.00

[a] MF: TE measured with respect to the meta-frontier (MF)

To further compare the TE measures obtained from the various models, rank correlation coefficients are calculated and reported in Table 6. All pair wise comparisons exhibit positive correlations, ranging from 0.44 between the TL model and the MF for Chile, and 0.85 for Uruguay. These results imply that although average TE varies across models, the ranking of farms with respect to their TE level tends to be fairly consistent.

5 Summary and concluding comments

The objective of this paper was to compare technical efficiency (TE) for dairy farms in Argentina, Chile and Uruguay using the Meta-Frontier (MF) approach developed by Battese and Rao (2002) and refined by Battese et al. (2004) and O'Donnell et al. (2008). The analysis is developed using a single-output/multi-input technology. The data are highly unbalanced panels including a different number of farms and periods for the various countries. The Argentinean case covers 46 dairy farms, three periods (1997/1998, 1999/2000 and 2001/2002), and 82 observations. The Chilean case has 48 dairy farms, five periods (1996/1997, and 1998/1999 through 2001/2002), and 92 observations. The Uruguayan data has 70 dairy farms, four periods (1999/2000 through 2002/2003), and 147 observations.

Thus, the pooled dataset contains a total of 164 farms and 321 observations, and spans a 7 year period.

TE measures are obtained from Stochastic Production Frontier (SPF) models estimated separately for each country and pooled for all three countries. In addition, an MF model is estimated with the pooled data using linear programming. Alternative specifications using the Cobb-Douglas (CD) and translog (TL) functional forms, and the half-normal and truncated-normal distributions for the one-sided error term were evaluated and the inefficiency error term was modeled following the Battese and Coelli (1992) approach. Various statistical tests were performed to obtain the best model for the data under analysis. The specification tests for all SPF models for each country and for the pooled data reveal that the TL is the most appropriate functional form, the inefficiency effects display a half-normal distribution, and TE is statistically significant and time invariant.

The null hypothesis that the dairy farms from the three countries operate on the same production frontier is strongly rejected, which implies that the production frontier estimated from the pooled data should not be used to compare TE across countries. Instead, comparisons need to be made with respect to a function that envelopes the three individual country frontiers, which is the concept that underlies the MF framework. Thus, there are two kinds of frontiers estimated, the individual country frontiers and the MF. The difference or gap between these two frontiers for a given country is referred to as the Metatechnology Ratio (MTR).

The average MTRs for Argentina, Chile and Uruguay are 83.8, 79.6 and 91.4%, respectively, and these results are significantly different from each other. Hence, the Uruguayan frontier is the closest to the MF while the Chilean is the most distant, and Argentina is in an intermediate position.

The average TE estimates for the preferred country specific SPF models are 87.0, 84.9 and 81.1%, respectively, for Argentina, Chile and Uruguay, which are consistent with TE values for dairy farms reported in the literature (Bravo-Ureta et al. 2007). However, these TE measures are not directly comparable as previously indicated. Instead, a direct comparison should be made based on the MF which shows lower average TE levels: 72.8, 65.8 and 73.4% for Argentina, Chile and Uruguay, respectively. The average TEs for Argentina and Uruguay are not significantly different from each other and both are higher than the value for Chile. It is important to point out that if TE is compared across the three countries based on a pooled stochastic frontier, the TE averages are equal for the three countries. Therefore, it is important to exercise care when comparing performance across countries (groups) because the reference frontier used can yield significantly different results.

All frontier models presented in this paper exhibit increasing returns to size (RTS), with average function coefficient values for the preferred SPF models equal to 1.231 for Argentina, 1.100 for Chile, 1.068 for Uruguay, and 1.115 for the Meta-Frontier. These RTS measures imply that on average dairy farms in the three samples are operating at a sub-optimal size, which further suggests continued structural changes in the industry toward fewer but larger farms. Moreover, unless specific policies are adopted, such changes would probably accelerate particularly if trade liberalization intensifies as farmers would be forced to expand their operations in pursuit of lower average costs and higher profits.

A noteworthy implication of the analysis reported in this paper is that to contrast farm productivity from data coming from different countries, especially for countries that are neighbors and can easily share technologies and experiences, the MF appears to be a valid approach for such comparative work. This procedure seems even more relevant in the current environment of growing market liberalization, because farmers are forced to compete with their peers from other countries.

It is important to indicate that the results of this paper are based on panel data sets collected for Argentina, Chile and Uruguay; thus, the analyses and outcomes presented above are specific to the time period and dairy farms in which the data were collected. Ideally, researchers would have national representative panel data sets from the various countries to undertake this work. Clearly, these types of data are very scarce and in the case of South America almost non-existent. More cross-country cooperation, particularly among neighboring countries, is needed to improve this situation.

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