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A STUDY OF DAIRY FARM TECHNICAL EFFICIENCY USING META-REGRESSION: AN INTERNATIONAL PERSPECTIVE

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ABSTRACT

This paper develops a meta-regression analysis to explain the variation of mean technical efficiency (PETP) measurements from a total of 65 frontier studies that report technical efficiency (ET) measurements at the dairy farm level in the literature published in English and Spanish. The analysis includes the effect of methodology on ET measurements, as well as the effect of the econometric procedure on the meta-regression estimates. Eight models were estimated, and two of these were selected: a fixed effects specification with dummy variables for the most significant studies without geographical effects (EFS), and a specification where the multiple observations are averaged and geographical effects included (OP). Based on model performance, the EFS option is chosen for the analysis. The results of the EFS model suggested that non-parametric deterministic models generate higher PETP estimates than the parametric cases (stochastic and deterministic frontier models). In addition, the Cobb-Douglas and translog forms yield higher average PETP than all other functional forms, cross-sectional data produce higher ET estimates than panel data, and the PETP is higher when the study is input-oriented. The primal approach implies a higher ET estimate than the dual analysis, and when more variables are included in the model, the PETP value is higher.

Key words: meta-regression, frontier models, technical efficiency, dairy farms.

INTRODUCTION

In an environment of growing liberalization, productivity growth, which is a major element of competitiveness, is essential to insure the prosperity of agriculture in general and dairy farming in particular (Sandrey and Scobie, 1994; Pinstrup-Andersen, 2002; Ruttan, 2002). A clear example is New Zealand, which opened its economy to the world market at the beginning of 1984 and then experienced a clear improvement in farm technical efficiency (ET henceforth) (Sandrey and Scobie, 1994; Evans *et al.*, 1996; Paul *et al.*, 2000). This improvement in ET has occurred as New Zealand has experienced a marked increase in the value of dairy products exported (Blayney and Gehlhar, 2005). The measurement of ET is important because it can help in both policy formulation and farm management (Russell and Young, 1983; Kalirajan, 1984; Bravo-Ureta and Rieger, 1991). Producers benefit directly from improvements in their technical performance because more efficient farms tend to generate higher incomes and thus have a better chance of surviving and staying in business (Bravo-Ureta and Rieger, 1991; Dartt *et al.*, 1999; Lawson *et al.*, 2004).

In the past decades, many researchers have developed and applied diverse methods to evaluate ET at the farm level. Battese (1992), and Bravo-Ureta and Pinheiro (1993) reviewed selected articles in order to derive general conclusions about the range of ET and the performance of the methodologies reviewed. Rivas (2003) applied a meta-regression analysis to describe the behavior of ET for a limited group of dairy farm studies listed in selected databases in the English language literature. More recently, Bravo-Ureta *et al.* (2007) developed a meta-regression analysis of ET measures for all agricultural activities which includes 167 farm level studies from around the world.

In this paper we contribute to the existing literature by undertaking a meta-regression analysis focused on dairy farm ET. Thus, we examine the impact of various attributes of a dairy efficiency study (e.g., estimation technique, functional and sample size, among others)

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on ET estimates. In our analysis we also account for the possible lack of data independence stemming from the presence of multiple observations from the same study.

MATERIALS AND METHODS

Data collection

A systematic search was made for dairy farm studies published in both English and Spanish between January 1986 and January 2006 in the following databases: Agricola; Agris International; Econlit; Factiva; Infotrac; Ingenta; JSTOR; ProQuest; Social Science Citation Index; Science Direct; Web of Knowledge; Web of Science; and the World Agricultural Economics and Rural Sociology Abstracts. A complementary search was performed in the following web databases: Blackwell Synergy; EconPapers; Scielo; SpringerLink; and Taylor & Francis. In addition, a search was performed in the following Spanish language literature sources: Dialnet (online database); Agrociencia (Mexico and Uruguay); Ciencia e Investigación Agraria (Chile); Cuadernos de Economía (Chile and Colombia); Economía Agraria y Recursos Naturales (Spain); Estudios de Economía Aplicada (Spain); Investigación Agraria, Producción y Sanidad Animales (Spain); Producción Animal (Spain); Revista Brasileira de Economía (Brazil); Revista de Análisis Económico (Chile); Revista Española de Estudios Agrosociales y Pesqueros (Spain); and Revista de Estudios Agrosociales (Spain).

Variable Definition and Empirical Models

The frontier function methodology, as introduced in the path breaking paper published by Farrell just over 50 years ago (1957), uses the efficient unit isoquant to measure economic efficiency (EE), and to decompose this measurement into ET and allocative efficiency (AE). In this model, ET is defined as the ability of the firm to produce maximum output given a set of inputs and the technology. AE measures the success of the firm in choosing the optimal input proportions, i.e., where the ratio of marginal products for each pair of inputs is equal to the ratio of their market prices. In Farrell's framework, EE is a measurement of overall performance and is equal to ET times AE (EE = ET x AE). These concepts are illustrated in Figure 1, where point P represents an inefficient firm and the distance QP is the amount by which all inputs could be reduced (proportionally) without lowering output to achieve the technically efficient level of production (point Q). Thus, the ET measurement is equal to the ratio 0Q/0P. Similarly, AE is equivalent to the ratio 0R/0Q.

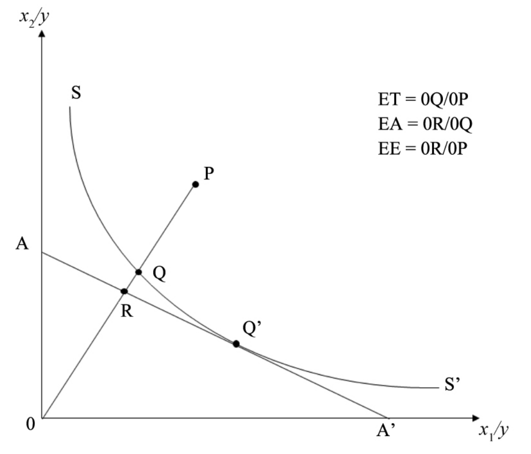
The working hypothesis of this paper is that the variation in average farm ET (PETP henceforth) for dairy farms in published studies can be explained by the major attributes of the models used. For this purpose, the following two base models are estimated:

Base Model A: PETP = *f* (PEST, PDET, TL, CD, CTR, PROD, PRI, VAR, VAROBS) [1]

Base Model B: PETP = *f* (Model A, plus INDIA, NAMR, AFRI, LATIN, ESTE) [2]

The dependent variable in the meta-regressions is the PETP measurement reported in the studies included in the data set. The independent methodological variables are: PEST, a dummy equal to one if the model is a parametric stochastic frontier, and zero otherwise; PDET, a dummy equal to one if the model is a parametric deterministic frontier, and zero otherwise, the omitted category being non-parametric deterministic studies; TL, a dummy equal to one if the TL functional form is used; CD, a dummy equal to one for the CD functional form Cobb-Douglas (CD) and the excluded category is other functional forms and non-parametric studies; CTR, a dummy equal to one if the data is cross-sectional, and zero if panel data; PROD, a dummy equal to one if the model is output-oriented, and zero if input-oriented; PRI, a dummy equal to one if a primal model is estimated, and zero for dual models; VAR, the number of explanatory variables; and VAROBS, the ratio between VAR and the number of observations used in a study.

In Base Model B, the following set of regional variables is incorporated: INDIA, which is a regional dummy variable equal to one if the study used data for that part of the world, and zero otherwise; NAMR, a dummy equal to one if the data comes from North America (United States and Canada), and zero otherwise; AFRI, a dummy equal to one if the study used data from Africa, and zero



Source: Coelli *et al.* (2005).

Figure 1. Technical (ET), allocative (EA) and economic efficiency (EE) for an input oriented model.

otherwise; LATIN, a dummy equal to one if the study used data from Latin America, and zero otherwise; and, ESTE, a dummy equal to one if the study used data from Eastern Europe, and zero otherwise. The omitted regions are Western Europe and Oceania.

Meta-studies often incorporate articles that include several observations, which gives rise to a potential lack of independence in the data because studies with a higher number of observations have more weight in the analysis (Anderson and Weitz, 1989; Van Den Bergh *et al.*, 1997). Several econometric procedures have been proposed to deal with this issue. Phillips (1994) applied fixed effects, while Verlegh and Steenkamp (1999) used a two step process following a procedure suggested by Anderson and Weitz (1989). Another approach is to average the data according to some specified criteria (Espey *et al.*, 1997; Verlegh and Steenkamp, 1999; Johnston *et al.*, 2003; Hunter and Schmidt, 2004). Including a dummy variable to capture the study (fixed) effect to address the multi author problem (Anderson and Weitz, 1989) has been criticized by Verlegh and Steenkamp (1999), who argue that incorporating study dummies in a meta-regression model is likely to introduce severe multicollinearity. To avoid the collinearity problem, Anderson and Weitz (1989) suggest a two step procedure. First, the model without study dummies is estimated and the residuals from this step are used as the dependent variable in a second regression. In this second step, the study dummies are regressed on the residuals from the first step using a stepwise procedure. If the residuals are "white noise" then there are no study effects, and if not, then the selected dummies are introduced into the original model, which is re-estimated.

Another problem that arises when studies have multiple estimates, and thus the observations lack independence, is a possible bias in the standard errors of the meta-regression parameters, which would invalidate tests of hypotheses (Espey *et al.*, 1997; Verlegh and Steenkamp, 1999; Johnston *et al.*, 2003; Hunter and Schmidt, 2004). One option to mitigate this problem is to average multiple observations from a given study. This can be done in various ways (Hunter and Schmidt, 2004). In this paper, the presence of multiple PETP is due to the diversity of attributes used in the estimation of ET and all the main attributes are included in the base Models A and B. However, some attributes are incorporated in only a few models within a study and in such cases we average the respective ET measurements.

To deal with the various issues discussed above, three additional models (1, 2 and 3) are estimated for each base Model (A and B), yielding a total of eight estimated models: 1) Models with full fixed effects; 2) Models with selected fixed effects; and 3) Models with averaged multiple observations. Models with full fixed effects and with selected fixed effects include a set of dummy variables that are defined for each study that reports two or more PETP estimates. Each study dummy is equal to 1 for all the observations that belong to a given study, and zero otherwise. Models with full fixed effects include all study dummies available, while models with selected fixed effects include only the selected study dummies following the two step procedure suggested by Anderson and Weitz (1989), as previously detailed.

ET scores are bounded between zero and one; thus, the two-limit Tobit procedure should be used (Greene, 2003). However, the meta-analysis literature focusing on ET in the agricultural sector reports similar results for the Tobit and Ordinary Least Square (OLS) procedures. Another consideration articulated by Stanley and Jarrell (1989) is that meta-regression studies use different data sets, different sample sizes, and different independent variables, which suggest that the variances of the meta-regression coefficients may not be equal, which implies that meta-regression errors are likely to be heteroskedastic. Therefore, in the current study all meta-regressions are estimated using White's heteroskedastic consistent covariance matrix estimation to correct the estimates for an unknown form of heteroskedasticity. This procedure is readily available in the Shazam Econometrics Software (Whistler *et al.*, 2001) and has been used in other meta-analysis work (Johnston *et al.*, 2003; Bravo-Ureta *et al.*, 2007).

RESULTS AND DISCUSSION

The literature search generated a total of 65 published papers which contain the type of information required for the present research. Because many of the papers report multiple ET estimates, the meta-dataset consists of a total of 329 observations. Table 1 presents an overview of all papers used in this assessment, including the authors, year of publication, country, and the PETP reported. In addition, all these papers are classified by the methodology implemented in the studies. To simplify the table, for studies that report more than one estimate using the same methodology, the average figures are included.

Table 2 presents the methodological features of the studies included in this research. As indicated, a total of 65 studies are included out of which 38 apply deterministic models and 33 stochastic models. It is important to mention that the total number of papers with stochastic and deterministic models (71) is larger than the reported number of papers (65) because in some studies both techniques are implemented. All studies combined yield a total of 329 observations given that, as already stated, some authors report multiple estimates. The data show a similar number of observations and studies that use

Table 1. Overview of empirical studies of average mean technical efficiency (PETP) for dairy farms.

Author(s). (Year). Journal, Country[1]	Number of measurements[2]	Sample size (Number of farms)	PETP (%)
I. No-Parametric			
Deterministic frontier			
Arzubi and Berbel (2001), Rev. Esp. Estud. Agrosoc. Pesq., Argentina	3	35	77.8
Arzubi and Berbel (2002), Invest. Agrar. Prod. Sanid. Anim., Argentina	6	42	87.5
Arzubi *et al.* (2004), Rev. Argent. Econ. Agrar., Argentina	1	45	90.5
Asmild *et al.* (2003), J. Prod. Anal., Netherlands	2	1808	80.5
Cloutier and Rowley (1993), Can. J. Agric. Econ., Canada	2	187	89.8
Fraser and Cordina (1999), Agric. Syst., Australia	6	50	88.5
González *et al.* (1996), Invest. Agrar. Econ., Spain	8	56	77.9
Jaforullah and Whiteman (1999), Aust. J. Agric. Resour. Econ., New Zealand	1	264	89.0
Kaliba (2004), Q. J. Int. Agric., Tanzania	8	240	75.9
Lachaal *et al.* (2002), Mediterr. J. Econ. Agric. Environ., Tunisia	1	17	68.0
Mathijs and Vranken (2001), Post Communist Econ., Hungary	3	26	42.3
Pardo *et al.* (2002), Empir. Econ. Lett., Spain	5	38	65.2
Piesse *et al.* (1996), J. Comp. Econ., Slovenia	4	272	86.0
Reinhard *et al.* (2000), Eur. J. Oper. Res., Netherlands	8	1535	79.7
Silva *et al.* (2004), New Medit, Portugal	2	122	66.6
Tauer (1993), Agric. Resour. Econ. Rev., USA	2	395	78.3
Tauer (1998), J. Agric. Econ., USA	6	630	90.0
Thirtle *et al.* (1996), J. Prod. Anal., Slovenia	34	136	77.9
Thomas and Tauer (1994), Can. J. Agric. Econ., USA	4	125	89.2
Weersink *et al.* (1990), Can. J. Agric. Econ., Canada	1	105	94.9
Average			**78.8**
Stochastic frontier			
Haghiri *et al.* (2004), Appl. Econ., Canada	12	1021	58.2
Average			**58.2**
II. Parametric			
Deterministic frontier			
Ahmad and Bravo-Ureta (1996), J. Prod. Anal., USA	5	1072	76.5
Álvarez *et al.* (1988), Rev. Estud. Agro-soc., Spain	1	154	40.0
Álvarez and González (1999), Am. J. Agric. Econ., Spain	1	410	72.0
Álvarez and Arias (2004), Agric. Econ., España	1	1176	70.0
Arias and Álvarez (1993), Invest. Agrar. Econ., Spain	1	336	73.0
Bravo-Ureta (1986), Can. J. Agric. Econ., USA.	1	222	82.2
Bravo-Ureta and Rieger (1990), J. Agric. Econ., USA	6	404	63.3
El-Osta and Morehart (2000), Rev. Agric. Econ., USA	3	679	87.0
Haghiri and Simchi (2003), Empir. Econ. Lett., USA.	1	210	67.4
Hallam and Machado (1996), Eur. Rev. Agric. Econ., Portugal	3	340	66.3
Karagiannis *et al.* (2002), J. Prod. Anal., U.K.	22	2147	70.4
Lachaal *et al.* (2003), Eur. Assoc. Anim. Prod., Tunisia	1	61	75.0
Maietta and Sena (2000), Eur. Rev. Agric. Econ., Italy	1	533	55.0
Orea *et al.* (2004), J. Prod. Anal., Spain	3	445	65.9
Piesse *et al.* (1996), J. Comp. Econ., Slovenia	4	272	56.0

Continuated Table 1.

Poe and Jones (1992), J. Am. Soc. Farm Manag. Rural Appraisers, USA	4	675	74.8
Richards and Jeffrey (2000), J. Agric. Resour. Econ., USA	1	181	94.2
Tauer and Belbase (1987), Northeastern J. Agric. Resour. Econ., USA	1	432	69.3
Turk (1995), Zb. Bioteh. Fak. Univ. Ljubl. Kmet. Supl., Slovenia	2	272	78.0
Average			**70.1**
Stochastic frontier			
Ahmad and Bravo-Ureta (1996), J. Prod. Anal., USA	12	1072	81.0
Arias and Álvarez (1993), Invest. Agrar. Econ., Spain	1	336	82.0
Bailey *et al.* (1989), West. J. Agric. Econ., Ecuador	1	68	78.1
Battese and Coelli (1988), J. Econom., Australia	2	336	70.0
Bravo-Ureta and Rieger (1990), J. Agric. Econ., USA	2	404	83.9
Bravo-Ureta and Rieger (1991), Am. J. Agric. Econ., USA	1	511	83.0
Brümmer and Loy (2000), J. Agric. Econ., Germany	1	5093	96.0
Brümmer (2002), Am. J. Agric. Econ., Germany, Netherlands and Poland	12	300	86.9
Cuesta (2000), J. Prod. Anal., Spain	5	410	82.7
Dawson (1987), Eur. Rev. Agric. Econ., U.K.	3	434	85.3
Dawson (1988), Oxf. Agrarian Stud., U.K.	1	406	81.0
Dawson (1990), Oxf. Agrarian Stud., U.K.	3	306	86.9
Dawson and Wales (1990), Appl. Econ., U.K.	3	306	85.7
Dawson and Woodford (1991), Oxf. Agrarian Stud., U.K.	1	918	86.0
Ghosh *et al.* (1994), Forecast. Soc. Change, USA	1	145	91.9
Haghiri and Simchi (2003), Empir. Econ. Lett., USA	1	210	83.1
Hallam and Machado (1996), Eur. Rev. Agric. Econ., Portugal	1	340	88.0
Heshmati (1998), Appl. Econ., Sweden	1	3979	94.5
Heshmati and Kumbhakar (1994), J. Prod. Anal., Sweden	12	559	82.2
Jaforullah and Deblin (1996), N. Z. Econ. Pap., New Zealand	3	264	91.9
Kumbhakar *et al.* (1989), Rev. Econ. Stat., USA	6	89	72.2
Kumbhakar *et al.* (1991), J. Bus. Econ. Stat., USA	9	519	73.4
Kumbhakar and Heshmati (1995), Am. J. Agric. Econ., Sweden	13	4890	84.7
Lawson *et al.* (2004), Livest. Prod. Sci., Denmark	2	574	94.5
Lawson *et al.* (2004), J. Dairy. Sci., Denmark	2	514	92.8
Mbaga *et al.* (2003), Can. J. Agric. Econ., Canada	8	1143	94.8
Moreira López *et al.* (2006), Arch. Med. Vet., Chile	5	92	72.2
Pierani and Rizzi (2003), Agric. Econ., Italy	7	533	65.9
Reinhard *et al.* (1999), Am. J. Agric. Econ., Netherlands	2	1545	89.9
Reinhard *et al.* (2000), Eur. J. Oper. Res., Netherlands	8	1535	89.4
Reinhard and Thijssen (2000), Eur. Rev. Agric. Econ., Netherlands	11	2589	83.8
Saha and Jain (2004), Indian J. Agric. Econ., India	8	23	90.2
Average			**83.3**
OVERALL AVERAGE			**78.4**

[1] Full citations are not presented to save space and are available upon request from the authors. Journal titles are presented using ISO (International Organization for Standardization) abbreviations.
[2] Several studies report various measurements of ET stemming from the application of different methods.

Table 2. Summary of empirical studies of average mean technical efficiency (PETP) for dairy farms.

Category	Nº Obs.	Nº Studies[1]	Deterministic Average (Min-Max)	Sthocastic Average (Min-Max)	PETP[1]
Approach					
Parametric	210	46	**70.1** (40.0-94.2)	**83.3** (47.9-99.8)	**79.4**
Non-Parametric	119	21	**78.8** (39.0-100.0)	**58.2** (42.0-69.0)	**76.7**
Data					
Panel	207	30	**75.6** (46.0-94.2)	**79.7** (42.0-99.8)	**77.7**
Cross Sectional	122	35	**75.5** (39.0-100.0)	**84.9** (47.9-96.6)	**79.6**
Functional form[1]					
Cobb-Douglas	72	22	**73.0** (40.0-94.2)	**79.8** (47.9-92.5)	**77.9**
Translog	114	21	**69.5** (49.0-85.6)	**85.9** (60.9-99.8)	**81.2**
Others	24	5	**65.6** (46.0-79.7)	**81.3** (61.8-96.6)	**75.4**
Returns to scale					
Constant	129	39	**75.3** (39.0-100.0)	**76.3** (42.0-95.0)	**75.8**
Variable	200	38	**75.7** (46.0-94.9)	**85.0** (60.9-99.8)	**80.1**
Orientation					
Output	202	48	**73.1** (40.0-94.9)	**81.5** (42.0-99.8)	**78.7**
Input	127	26	**77.2** (39.0-100.0)	**80.8** (61.8-95.0)	**77.9**
Technology representation					
Primal	282	54	**75.6** (39.0-100.0)	**83.1** (42.0-99.8)	**78.9**
Dual	47	11	**75.6** (49.0-94.2)	**75.5** (47.9-88.5)	**75.5**
Language					
English	303	58	**75.1** (39.0-100.0)	**81.7** (42.0-99.8)	**78.4**
Spanish	26	7	**79.3** (40.0-92.5)	**73.8** (69.0-82.0)	**78.0**
Geographical region					
Africa	10	3	**75.1** (58.7-86.4)		**75.1**
India	8	1		**90.2** (86.6-92.5)	**90.2**
Latin America	16	5	**84.9** (76.9-92.9)	**73.2** (69.0-78.1)	**80.5**
North America[3]	89	19	**78.8** (45.9-100.0)	**75.9** (42.0-96.6)	**77.1**
Eastern Europe	47	4	**74.5** (39.0-93.0)		**74.5**
Western Europe and Oceania	159	33	**73.2** (40.0-90.8)	**84.2** (60.9-99.8)	**79.7**
Total average			**75.6** (39.0-100.0)	**81.4** (42.0-99.8)	**78.4**
Number of observations			**169**	**160**	**329**
Number of studies[2]			**38**	**33**	**65**

[1] Valid for parametric approach only.
[2] Several studies report various measurements of ET stemming from the application of different methods.
[3] North America includes the USA and Canada.

deterministic (169 observations) and stochastic models (160 observations). The PETP for all deterministic models is 75.6% compared to 81.4% for all stochastic models and this mean difference is statistically significant at 5%. In addition, most of the studies rely on the translog (TL) functional form, are output-oriented and are mainly published in English (58 out of 65).

Table 2 also summarizes the PETP measurements according to the geographical region where the studies were conducted. Western Europe and Oceania have the largest number of observations (159 in 33 studies), followed by North America (89 in 19 studies), Eastern Europe (47 in four studies), Latin America (16 in five studies), Africa (10 in three studies) and India (eight in one study). The highest PETP, when stochastic and deterministic studies are combined, is for India (90.2%), while the lowest is for Eastern Europe (74.5%).

Table 3. Meta-regressions of mean technical efficiency (PETP) for dairy farms.

Variables	**Selected fixed effects (EFS)**	**Averaged model (OP)**
Constant	67.524 ***	72.169 ***
	3.520 [a]	4.725
PEST, parametric stochastic frontier	-6.857	2.908
	4.256	5.006
PDET, parametric deterministic frontier	-18.855 ***	-9.098 *
	3.994	4.922
TL, translog	13.059 ***	2.770
	4.469	5.575
CD, Cobb-Douglas	15.117 ***	2.653
	4.244	4.834
CTR, cross-sectional	2.426 **	-1.706
	1.213	2.471
PROD, output-oriented	-2.456 *	-3.688
	1.256	2.852
PRI, primal model	9.137 ***	4.673
	2.968	3.449
VAR, number of explanatory variables	0.240 ***	0.264 *
	0.082	0.150
VAROBS, ratio between VAR and the number of observations	3.546	-5.107
	2.571	7.681
INDIA, India		14.378 **
		6.721
NAMR, North America		6.244 **
		2.821
AFRI, Africa		0.535
		5.866
LATIN, Latin America		5.595
		4.277
ESTE, Eastern Europe		-9.700 **
		4.380
Log-likelihood	-1.098.5	-450.7
R^2	0.6754	0.3726
Adj. R^2	0.6329	0.2897

*** Significant at 1%; ** Significant at 5%; * Significant at 10%.

[a] Figures in italics are robust standard errors.

PEST, dummy used if the model is a parametric stochastic frontier or not; PDET, dummy used if the model is a parametric deterministic frontier or not; TL, dummy used if the TL functional form is used; CD, dummy used for the CD functional form or not; CTR, dummy used if the data is cross-sectional or not; PROD, dummy used if the model is output-oriented or not; PRI, dummy used if a primal model is estimated or not; VAR, the number of explanatory variables; VAROBS, the ratio between VAR and the number of observations used in a study; INDIA, regional dummy variable if the study used data for that part or theworld or not; NAMR, dummy used if the data comes from North America (United States and Canada) or not; AFRI, dummy used if the study used data from Africa or not; LATIN, dummy used if the study used data from Latin America or not; and ESTE, dummy used if the study used data from Eastern Europe or not.

A preliminary analysis reveals that the two preferred options are the Selected Fixed Effects Model (Model EFS) that includes methodological variables, without geographical variables, and the Averaged Observations Model (Model OP) that incorporates both methodological and geographical variables. These two models are not nested, so no further formal statistical comparisons among them are undertaken. The parameters for both of theses models are included in Table 3 and a simple comparison of the number of significant parameters and adjusted R^2 reveals that model EFS is clearly superior to model OP. Therefore, the following analysis of the results is based on model EFS. Additional information for all models can be obtained directly from the authors.

The variables PEST and PDET capture the effect of the methodology used to estimate the frontier on PETP estimates where the excluded category for this group of dummies is the non-parametric approach. Model EFS has a negative parameter for PEST while in Model OP it is positive, but in both cases it is non significant. Theoretically, a positive value is expected for the parameter for PEST, given that deterministic models assume that all deviations from the frontier represent inefficiency (Coelli *et al.*, 2005). The estimated parameter for PDET suggests that parametric deterministic models yield lower PETPs than non-parametric models, which is valid in both models. This finding is also consistent with *a priori* expectations (Kumbhakar and Lovell, 2000). Thiam *et al.* (2001) found a negative and significant parameter for stochastic models compared to deterministic models in their research using 34 studies covering only developing countries. Bravo-Ureta *et al.* (2007) found a negative and significant parameter for both the parametric stochastic and deterministic models when compared with the non-parametric approach in their research using 167 studies on farming.

The TL and CD specifications are statistically significant in Model EFS, but not for Model OP. The CD and TL yield higher PETPs than other functional forms. These results suggest that the functional form has an unclear effect on PETP, which is consistent with what has been reported by Ahmad and Bravo-Ureta (1996), Resti (2000), and Bravo-Ureta *et al.* (2007), among others.

The parameter for CTR (Cross Sectional data) is positive and significant in Model EFS, which is consistent with the averages shown in Table 2, while the PROD parameter (orientation of the model) is negative. Thus, these findings suggest that frontier models using an output-oriented approach produce lower PETP estimates than models based on an input-oriented approach. Neither Thiam *et al.* (2001) nor Bravo-Ureta *et al.* (2007) include this variable in their meta-regressions.

Model EFS has a positive parameter for PRI, suggesting that the question of whether the model relies on a primal (PRI) or dual representation of the technology can have a significant effect on PETP. By contrast, Bravo-Ureta *et al.* (2007) found a non-significant effect for this variable.

The results indicate that the parameter for VAR (number of explanatory variables) is positive and significant and VARSIZE (ratio between the number of explanatory variables and the number of observations) is also positive but not significant. Thomas and Tauer (1994) reported an increase in the ET measurements in a non-parametric analysis when the number of variables is increased, which is consistent with the Bravo-Ureta *et al.* (2007) findings. In general and as would be expected, these results indicate a positive association between PETP and model dimensionality (Chavas *et al.*, 2005).

CONCLUSIONS

The empirical and the conceptual literature contain mixed results and contradictory views concerning the virtues of the various methodologies that have been developed to measure technical efficiency. This paper organizes studies originating from an extensive body of literature that has been published in English and Spanish over the past few decades on dairy farm ET. A total of 65 studies that use frontier models report PETP measurements at the farm level, and all the variables required for the estimated models are included. These studies yielded 329 observations, given that some report several PETP estimates.

Eight alternative models were estimated and several tests indicate that two of them perform better than the rest and thus are selected for further analysis. These two models are the selected fixed effects (model EFS) and the averaged multiple observations (model OP). Further analysis of the performance of these two models indicates that the EFS model is superior to the OP model. Thus, the results confirm the importance of considering the effect of multiple observations in the estimation of a meta-regression analysis.

The main results of the EFS model suggest that non-parametric deterministic models generate higher PETP estimates than the parametric cases (stochastic and deterministic frontier models). Within the parametric studies, the deterministic approach produces lower ET figures than the stochastic approach. The effect of functional form on ET is significant and the CD and TL forms yield higher average ET than all other functions. Frontier models based on cross-sectional data produce higher estimates than those based on panel data. In addition, the orientation of the study (input or output) has a significant effect, with a higher PETP measurement being found for the input-oriented cases. The primal approach implies a higher ET estimate than the dual analysis. Finally, the dimensionality of the model is relevant and when more variables are included in the model, a higher PETP value is reported.

RESUMEN

Un estudio de eficiencia técnica en lecherías usando meta-regresión: Una perspectiva internacional. El objetivo de este estudio es realizar un análisis de meta-regresión para explicar la variación en el promedio de eficiencia técnica predial (PETP) en 65 estudios, en la literatura en inglés y español, desarrollados con datos a nivel predial y que reportan medidas de eficiencia técnica (ET). El estudio analiza tanto el efecto de la metodología empleada en la medición de la ET como el procedimiento econométrico en la estimación de la meta-regresión. Se estimaron ocho modelos de los cuales se escogieron dos: efectos fijos seleccionados (EFS) que incluye variables metodológicas y variables dummy para los estudios más significativos, y observaciones promediadas (OP) que contiene tanto variables metodológicas como geográficas. Basado en su comportamiento, se eligió el primer modelo para el análsis. Los resultados del modelo EFS sugieren que las fronteras determinísticas no-paramétricas generan PETP más altos que las paramétricas estocásticas y determinísticas. Las formas funcionales Cobb-Douglas y translogarítmica generan PETPs más altos que otras formas funcionales, datos de corte transversal producen valores de ET más altos que los de panel, y el PETP es más alto cuando el estudio es orientado al insumo. Análisis basados en el primal revelan valores promedios de ET más altos que en el dual, y un mayor número de variables incluidas en el modelo implica un PETP mayor.

Palabras clave: meta-regresión, modelos de frontera, eficiencia técnica, lecherías.

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