Dynamic efficiency analysis of Spanish outdoor and Greenhouse Horticulture sector

FATIMA LAMBARRAA
Courant Research Center "PEG", University of Göttingen, Germany, Tel: +49 (0) 551 394428. Fax: +49 (0) 551 399866. E-mail: flambar@uni-goettingen.de

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I. Introduction

The horticulture sector plays a very important role in Spanish agriculture and economy. Their participation in the final agricultural production reached 37%, with an increase during the last 10 years by 16% (MARM, 2008). This sector represents an important source of employment generating a total of 450,000 AWU (Agricultural Work Unit), which is the half of the job generated by the entire Spanish agricultural sector. (MARM, 2008).

The main production area is concentrated in the Mediterranean area. Andalucía, Valencia, Murcia and Catalonia represent a 66.3% of the total area devoted to horticulture production. By importance, Andalusia produce 33% of horticulture product, followed by Castilla-La Mancha (12%) and Murcia (12%). The main vegetable crops grown in Spain are tomato (35% of total produced vegetables), pepper and melon (8% each one). The 54% of pepper production is cultivated in greenhouses, followed by 28% of tomato and 21 % of melon.

The most Spanish horticulture production is oriented to the exportation (40% of total production). In the second place, we find domestic consumption (32%), and then the transformation sector (17%). Vegetables account for 41.9% of exported volume, while the rest is represented by fruit (58.1%). The main exported products include tomato (almost one million tons), lettuce and pepper (about half a million tons each) and cucumber (400,000 tons).

The total Spanish area under horticulture crops is 406,688 ha, of which 301,399 ha are grown outdoors (74%) and 78,407 under glass. Most national area devoted to greenhouses are located in Andalucía (72%), located mainly in the Almeria province. Followed by Murcia (7.3%), Extremadura (5.4%), Canarias and Valencia (4% each). We notice the relevance of greenhouse vs. Outdoor inside each community. In the case of Andalusia and Canary islands, the greenhouse area presents 42% and 46% of the total area respectively. In Valencia and Murcia, this area presents 11 % and 12% respectively, while in Extremadura this area reaches 8.2%.

In this paper, dynamic technical efficiency is analyzed for both outdoor and greenhouse Spanish farms specialized in horticulture production. A dynamic stochastic frontier model is developed to estimate the long run technical efficiency and it persistence for both samples. The measurement of long-run technical inefficiency levels and its persistence helps us to evaluate the subsistence of farms over the long run and adjustment factors and forces leading to technical inefficiency.

The next section reviews the literature concerning dynamic efficiency and the methodological approach. Section 3 discusses the econometric specification and the empirical application. In section 4, we discuss main results. The last section is devoted to draw our conclusions.

II. Methodology

The majority of traditional stochastic frontier models tend to estimate frontier function and firm-specific inefficiency levels assuming that inefficiency levels are time-invariant (e.g. Schmidt and Sickles, 1984; Kumbhakar, 1987; and Greene, 2008). These studies do not allow for the explanation of time-varying efficiency levels through a formulation of production inefficiency that is impacted by behavioral or structural linkages over time. The change in efficiency is autonomous with the passing of time. Therefore, their technical efficiency models remain static and they fail to associate measurable evolution in technical efficiency with an economic motivation, giving a limited analysis of production slack.

Few stochastic frontier production studies account for dynamics in panel data models of technical inefficiency (e.g. Cornwell et al., 1990; Kumbhakar, 1990; Battese and Coelli, 1992; Lee and Schmidt, 1993 and Ahn and Schmidt, 1995). Such models aim to estimate the temporal pattern of time series variation in firm efficiencies levels. However, they are criticized by: a) the imposition of an arbitrary restriction on the short-run dynamic efficiency levels and, b) their incompatibility for the analysis of long-run dynamics on technical inefficiency.

Other studies, such as Ahn et al., (2000), allow firm specific technical inefficiency levels to follow an autoregressive process of order one (AR(1)). This approach does not require the imposition of the arbitrary restrictions on the short-run dynamic efficiency levels, but it is criticized by the absence of a theoretical justification. The authors claim that this is a useful approach to examine a dynamic link between technical innovations and production inefficiency levels by specifying an autoregressive processes implying the ability of firms to change systematically by a fixed percentage of their past-period inefficiency level. The limited number of studies focusing on this aspect about dynamic models efficiency (e.g. Ahn et al., 2002; Huang, 2004 and Tsionas, 2006) are justified by a complex likelihood function specification as well as the difficulties of assuming the inference on unobserved firm-specific inefficiencies (Tsionas, 2006).

The dynamic stochastic frontier models tend to estimate firms' long-run technical inefficiency level, given the pressure on a firm's ability to remain competitive in the long run unless they are technically efficient. Tsionas (2006) proposes that the inefficiency factors need to be adjusted by time which depends on adjustment costs. The higher the cost of adjustment; the greater the probability of finding evidence of persistent technical inefficiency. In this study, we consider a dynamic stochastic frontier model with persistent technical inefficiency over time using a parameter inferences and inferences on technical inefficiency on a firm-specific basis.

Several methods can be used to analyze technical efficiency in a production function. However, many researchers have shown that Bayesian approach may have, in some cases, several advantages over the classical econometric methods in applied research. It was found to be an excellent tool for making inference on efficiencies in stochastic frontier models (see e.g. Koop et al., 1994, 1997). Bayesian inference produces exact finite-sample posterior, predictive distributions and, formal treatment of parameter and model uncertainty (see e.g. Van den Broeck et al., 1994; Fernandez et al., 2003; Kim and Schmidt, 2000). However, the complexity of stochastic frontier models makes numerical integration methods inevitable. The most appropriate method in this context is Markov chain Monte Carlo (MCMC), as introduced by Koop et al. (1995).

Many applications have used this approach. Koop et al. (1995) and Osiewalski and Steel (1998) were the first that suggested the use of Bayesian methods for technical efficiency. They used a model with an informative prior for firm-specific intercepts. Such a model is similar to the classical fixed effects model assuming a distribution for inefficiency. We point out among others Van den Broeck et al., (1994) that used a sampling technique to obtain the posterior distribution for the Erlang model. Koop et al., (1995) that developed a Gibbs sampling approach. Greene (1990 and 2000) evaluates a complicated integral using numerical and Monte Carlo integration. More recently, Tsionas (2000, 2002 and 2006) and Kozumi and Zhang (2005), used a Gibbs sampling method to analyze the case of non-integer shape parameter.

The stochastic frontier production function with panel data can be expressed as follows (Tsionas, 2006):

$$y_{it} = x_{it}\beta + v_{it} - u_{it} \qquad i = 1,\dots,n, t = 1,\dots,T \qquad [1]$$

where x_{it} and β are a $k \times 1$ vector of regressors and parameters respectively.

v_{it} is a two-sided random errors that are assumed to be iid $IN(0,\sigma_v^2)$, $i = 1,\dots,n, t = 1,\dots,T$, and u_{it} is a vector of independently distributed and nonnegative random disturbances that represent technical inefficiency.

We assume that technical efficiency follows an autoregressive process:

$$\log u_{it} = z_{it}\gamma + \rho \log u_{i,t-1} + \xi_{it}, \text{ for } t = 2,\dots,T \qquad [2]$$

$$\log u_{i1} = z_{i1}\gamma/(1-\rho) + \xi_{i1}, \text{ for } t = 1 \text{ for all } i = 1,\dots,n. \qquad [3]$$

where $\xi_{it} \sim IN(0,\omega^2)$, for $t = 2,\dots,T$ is a random variable capturing the "unexpected log-efficiency sources" and $\xi_{i1} \sim IN(0,\omega^2/(1-\rho^2))$, for all $i = 1,\dots,n$. The "systematic part" $z_{it}\gamma + \rho \log u_{i,t-1}$ reflects "expected" log-inefficiency sources. z_{it} and γ are an $m \times 1$ vector of covariates and parameters, respectively. We assume that v_{it}, u_{it}, x_{it} and z_{it} are independent.

The joint density of the model is given by:

$$p(y,u \mid X,Z,\theta) = \int_{R_+^{nT}} p(y,u \mid X,Z,\theta)du$$

$$= (2\pi\sigma^2)^{-nT/2} \exp\left[-\frac{1}{2\sigma^2} \sum_{i=1}^{n} \sum_{t=1}^{T} (y_{it} + u_{it} - x_{it}\beta)^2 \right]$$

$$\times (2\pi\omega^2)^{-nT/2} \exp\left[-\frac{1}{2\omega^2} \sum_{i=1}^{n} \sum_{t=2}^{T} (\log u_{it} - z_{it}\gamma - \rho \log u_{i,t-1})^2 - \log u_{it} \right]$$

$$\times (1-\rho^2)^{n/2} \exp\left[-\frac{1-\rho^2}{2\omega^2} \sum_{i=1}^{n} (\log u_{i1} - z_{i1}\gamma /(1-\rho))^2 - \log u_{i1} \right]$$

[4]

The first line of the joint density comes from the normality of $y_{it} \mid x_{it}, u_{it}, \theta$, while the second come from log-normality of $u_{it} \mid z_{it}, u_{i,t-1}, \theta$, and the last one is due to lognormal assumption on $u_{i1} \mid z_{i1}, \theta$.

In order to carry out the Bayesian inference, the likelihood function is completed with a prior distribution $p(\theta)$ for location parameters[1] β, γ and ρ. The joint prior distribution is given by:

$$p(\beta,\gamma,\rho) = f_N^k(\beta \mid \overline{\beta}, \overline{V}_\beta) f_N^m(\gamma \mid \overline{\gamma}, \overline{V}_\gamma) p(\rho) \qquad [5]$$

$f_N^k(x \mid m,V)$ refers to the density of the k-variate normal distribution with mean vector *m* and covariance *V*. ρ has a Jeffreys´prior distribution[2] and is independent of γ, while scale parameter (σ and ω) are independent with inverted-gamma prior:

$$p(\varsigma) \alpha \varsigma^{-(n_\varsigma + 1)} \exp(-q_\varsigma /(2\varsigma^2)), \quad n_\varsigma \geq 0, q_\varsigma \succ 0 \qquad [6]$$

where ς refers to any of σ, ω, and n_ς, q_ς are parameters of the prior distribution.
An application of Bayes´ theorem by the multiplication of the *u* prior's given by [3] with the prior on structural parameters given in [5] and [6], gives a joint prior distribution involving θ and latent variables *u* (Tsionas, 2006):

$$p(\theta,u \mid y,X,Z) \,\alpha\, p(y,u \mid X,Z,\theta) \times p(\theta) \qquad [7]$$

where $p(y,u \mid X,Z,\theta)$ is the augmented likelihood function given in equation [6]. The high dimensional integral precludes a closed form solution to the likelihood function

[1] There are assumed to be independent of the scale parameters σ and ω.

[2] The Jeffreys´s prior in the context of a simple AR(1) model has a following density: $p(\rho) \alpha (1+\rho)^{-1/2} (1-\rho)^{-1/2}, -1 \prec \rho \prec 1$.

and thus, requires a numerical solution approach. Gibbs sampling[3] method with data augmentation has been used in order to make Monte Carlo draws from the joint posterior distribution of the model and to perform the computations (Gelfand and Smith, 1990).

Using the conditional distribution of $u_{it} | \theta, y, X, Z$ provided by Markov Chain Monte Carlo (MCMC) scheme, the technical efficiency is measured for each farm (Van den Broeck et al., 1994, Koop and Steel, 2001).

III. Empirical application

The dynamic stochastic frontier model has been estimated using a balanced panel data of 126 and 90 Spanish greenhouse and outdoor horticulture farms respectively. Those farms were observed during 6 years from 1999 to 2004.

Even though our analysis is based on farm-level data, aggregate measures are used to define some variables that are unavailable from the FADN dataset. Input and output price indices are necessary to deflate all monetary variables which are derived from Eurostat (Eurostat, 2011) using 2000 as the base year.
The dynamic stochastic functional form is specified as Translog functional form that takes the form:

$$\ln y_{it} = \beta_0 + \sum_{k=1}^{K} \beta_k \ln x_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{s=1}^{K} \beta_{ks} \ln x_{k,it} \ln x_{s,it} + \beta_T t + \frac{1}{2}\beta_T t^2 + \sum_{k=1}^{K} \beta_T t \ln x_{kit} + v_{it} - u_{it} \quad [8]$$

where k, j = 1,…,K indicate the conventional inputs used in the production process.

Production y_{it} is defined as an implicit quantity index by dividing total horticulture sales in currency units by the price index. Vector x_{kit} is defined as a (*1x6*) vector composed of five inputs and a time trend (*t*). Input variables are labor (x_L), defined as total hours spent on farm work, expenditure on fertilizers (x_F), pesticides (x_P), and other inputs such as plants costs and farming overhead (x_I). The total area of horticulture defines the land variable x_{LND}.

Vector z_i, in the technical inefficiency effects function, is a (*1x3*) vector that specifies the variables age and farm size. The older farmers are expected to be less efficient in comparison to younger ones (Battese and Coellli, 1995). The farm size is represented by the log of total area and its square (e.g. Gianakas et al., 2003; Alvarez and Arias, 2004 and Tsionas, 2006), since scale effects might be important in explaining technical

[3] Gibbs sampling is an iterative approach that permit making draws from a joint distribution by doing an iterated sequential draws from the conditional distributions.

efficiency. A statistical package GAUSS 7 has been employed to estimate the dynamic stochastic frontier model.

IV. Results and discussion

The results derived from the estimation of the Translog dynamic stochastic frontier model for both samples; outdoor and greenhouse farms are presented in Table 1. First-order parameters β_k of labor (except for greenhouse farms) and other inputs are positive and statistically significant, indicating that the production is increasing in such inputs.

The time trend is positive and statistically significant in the case of greenhouse farms, which suggests that the technology embodied in the greenhouse horticulture is changed with time. Therefore, any growth taking place over time is from new technologies implemented and can be added over time, which essentially means that there is an additional technical change effect.

The estimation result of the gamma component reveals that age and size variable included in Gamma 1 component for outdoor horticulture are significant. This result implies that technical inefficiency increases at a decreasing rate for larger farms. Moreover, younger farmer are more efficient relative to elderly ones, which means that younger farmers are more prone to introduce changes in farm management techniques.

The posterior means for the autoregressive component are 0.93 and 0.99 for outdoor and greenhouse farms respectively. This result shows that the autoregressive components for both cases are high and very close to unity which suggests that a big quantity of technical inefficiency is transmitted to the next time period, and the technical inefficiency is highly persistent in this sector.

Table 1. Results for dynamic stochastic frontier model using Translog functional form

Production frontier model		
Parameter (equation 1)	**Outdor horticulture**	**Greenehouse horticulture**
constant	-3.9597 (4.3478)	0.7141 (4.3813)
Labor	1.8158 (1.2444)*	0.4574 (1.1340)
fertilizers	0.4893 (0.5993)	-0.3005 (0.6535)
pesticides	-2.1764 (0.6523)***	-0.1311 (0.7478)
Land	-0.3893 (1.2904)	-3.0224 (1.7006)**
Other inputs	1.3024 (0.7067)**	1.1130 (0.7478)*
Labor* labor	-0.2426 (0.1925)	-0.0459 (0.1575)
Labor* fertilizers	-0.0600 (0.0882)	0.0924 (0.0949)
Labor* pesticides	0.3571 (0.0966)***	-0.0876 (0.1046)
Labor* land	0.4177 (0.1886)**	0.0591 (0.1979)
Labor* Other inputs	-0.2856 (0.1217)***	-0.0015 (0.1081)
fertilizers * fertilizers	0.0117 (0.0635)	0.0177 (0.0903)
Fertilizers* pesticides	0.0630 (0.0351)**	0.1069 (0.0683)*
Fertilizers* land	0.1054 (0.0754)*	0.0228 (0.0809)
Fertilizers* Other inputs	-0.0576 (0.0640)	-0.1855 (0.0883)**
pesticides * pesticides	0.1409 (0.0517)***	0.01522 (0.0838)
Pesticides* land	-0.3135 (0.0947)***	0.1820 (0.1059)**
Pesticides* Other inputs	-0.2254 (0.0781)***	-0.0038 (0.0907)
land * land	-1.3177 (0.3159)***	1.0054 (0.2848)***
land * Other inputs	0.0386	0.2486

	(0.1160)	(0.1640)*
Other inputs * Other inputs	0.2497 (0.0780)***	-0.0492 (0.0605)
trend	0.1917 (0.1951)	-0.1804 (0.1897)
Trend* trend	0.0030 (0.0125)	0.0332 (0.0132)***
Trend* labor	-0.0069 (0.0258)	0.0014 (0.0268)
Trend* fertilizers	-0.0291 (0.0156)**	-0.0561 (0.0215)***
Trend* pesticides	0.0609 (0.0181)***	0.0642 (0.0186)***
Trend* land	0.0093 (0.0235)	-0.0236 (0.0298)
Trend* Other inputs	-0.0564 (0.0230)***	0.0067 (0.0226)
Dynamic Technical efficiency model		
Parameter (equation 2)		
constant	-0.4151 (0.4404)	-0.3687 (0.6344)
size	-0.0196 (0.0123)	-0.0150 (0.0615)
(size)2	0.0002 (0.0003)	-0.0027 (0.0096)
age	0.009 (0.0073)*	0.0023 (0.0105)
Parameter (equation 3)		
Constant_1	-5.6687 (1.6436)***	-0.44084 (1.7509)
Size_1	0.0614 (0.0287)**	-0.0340 (0.2131)
(size)2_1	-0.0013 (0.0006)**	-0.0019 (0.0231)
Age_1	0.0564 (0.0266)**	-0.0250 (0.0259)
sigma	0.2557 (0.0160)***	0.3638 (0.0126)***
Omega (ω)	1.0304 (0.1559)***	0.6178 (0.2958)***
Omega_1	1.3056 (0.2333)***	0.9372 (0.2237)***
Rho (ρ)	0.9307 (0.0722)***	0.9942 (0.0721)***

Note: ***, ** and * indicate that the parameter is significant at the 1%, 5% and 10% respectively.

The comparison of our results with previous studies shows a similarity with Tsionas (2006), that had a persistence component close to 1, indicate that the technical inefficiency of Spanish horticulture farms are highly persistent, which suggests a high cost of adjustment as well as strong competition in this sector.

Table 2 shows estimated technical efficiency scores over the years for both samples. The predicted technical efficiency takes an average value of 77.3% and 89.2% for outdoor and greenhouse horticulture farms respectively. The static efficiency level of greenhouse farms is higher than outdoor farms by approximately 12 percentage. This difference can be explained by the use of high technology and the best control of use of different inputs in the case of greenhouse horticulture.

The analysis of the evolution of technical efficiency during the period studied shows an improvement of efficiency level of greenhouse farms by 15%. While, we point out a decrease of efficiency level by 11% in the case of outdoor horticulture farms during the same period. Those results can be explained by the technical change effect that improves efficiency level along year in the case of greenhouse horticulture.

Table 2. Evolution of Technical efficiency scores for outdoor and greenhouse horticulture farms (1999-2004)

	1999	**2000**	**2001**	**2002**	**2003**	**2004**
Outdoor horticulture	0.8329	0.8108	0.7894	0.7363	0.7338	0.7348
greenhouse horticulture	0.8156	0.8587	0.8914	0.9153	0.9291	0.9440

Results of the dynamic efficiency are reported in Table3. The measures of the long- run predicted technical efficiency in the case of outdoor and greenhouse horticulture farms are 17.16% and 15.59% respectively. We notice a very low predicted level of Long- run technical efficiency for both samples. However, these results are not surprising since the persistence parameter is high in both cases. Thus the difference of technical efficiency between static and dynamic frontier is very large for both samples. These results imply that the persistence of inefficiency of Spanish horticulture farms is strongly persistent over time.

Table 3. Static and Dynamic Technical Efficiency for outdoor and greenhouse horticulture farms

	Outdoor horticulture		**Greenhouse horticulture**	
	Static model	**Dynamic model**	**Static model**	**Dynamic model**
Mean	0.7730	0.1716	0.8923	0.1559

V. Conclusion

The purpose of this paper is the evaluation of dynamic technical efficiency for both outdoor and greenhouse Spanish farms specialized in horticulture production. A dynamic stochastic frontier model is developed to estimate the long run technical efficiency and it persistence for both samples. This analysis has been applied to 126 and 90 Spanish greenhouses and outdoor horticulture farms respectively using FADN data set. Those farms were observed during 6 years from 1999 to 2004.

The static efficiency level of greenhouse farms is higher than outdoor farms by approximately 12 percentage. The evolution of the static efficiency level during the studied period shows an increase by 15% in the greenhouse farms comparing to a decrease by 11% for outdoor horticulture farms. This difference can be explained by a best control of the use of different inputs in the case of greenhouse horticulture as well as the implantation of high technology that improves efficiency level over years.

The empirical results show a big difference of technical efficiency level between static and dynamic case for both samples. These results are consistent with the high value of the technical inefficiency persistence parameter for both cases which suggests that the technical inefficiency is highly persistent and shows a strong competition in this sector.

VI. References

Ahn, S.C., and P., Schmidt .1995. Efficient estimation of models for dynamic panel data. Journal of Econometrics 68: 5-27.

Ahn, S.C., D.H., Good, and R., Sickles. 2000. Estimation of Long-Run Inefficiency Levels: A Dynamic Frontier Approach. Eonometric reviews 19(4): 461-492.

Ahn, S.C., D.H., Good, and R., Sickles. 2002. Estimation of long-run inefficiency levels: a dynamic frontier approach.

Alvarez, A., and C., Arias. 2004. Technical efficiency and farm size: a conditional analysis. Agricultural Economics 30: 241-250.

Battese, G. E., and T. J., Coelli. 1992. Frontier Production Function, technical efficiency and panel data: with application to Paddy Farmers in India. Journal of Productivity Analysis 3: 153-169.

Battese, G.E., and T., Coelli. 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empirical Economics 20(2), 325-332.

Cornwell, C., P., Schmidt, and R.C., Sickles. 1990. Production Frontiers with Time-Series Variation in Efficiency Levels. Journal of Econometrics 46: 185-200.

EUROSTAT, 2011. Agricultural prices and prices indices. Dataset. Available at http://epp.eurostat.cec.eu.int. [1 January 2011].

Fernandez, C., G., Koop and M.F.J., Steel. 2003. Alternative Efficiency Measures for Multiple-Output Production. Working paper. Acceded January 2008. http://personal.strath.ac.uk/gary.koop/fks3new.pdf.

Gelfand, A., and A.F.M., Smith. 1990. Sampling-based approaches to calculating marginal densities. Journal of the American Statistical Association 85:398-409.

Giannakas, K., C.K., Tran, and V., Tzouvelekas. 2003. On the choice of functional form in stochastic frontier modeling. Empirical Economics (28) :75–100.

Greene, W. H. 1990. A gamma-distributed stochastic frontier model. Journal of Econometrics 46: 141–163.

Greene, W. H. 2000. Simulated likelihood estimation of the normal-gamma stochastic frontier function. New York University.

Greene, W. H. 2008. The econometric approach to efficiency analysis, in The Measurement of Productive Efficiency and Productivity Change, edited by H. O. Fried, C. A. K. Lovell, S. S. Schmidt, Oxford University Press.

Huang, H. C. 2004. Estimation of technical inefficiencies with heterogeneous technologies. Journal of Productivity Analysis 21 (3): 277–296.

Kim, Y., and O., Schmidt. 2000. A review and empirical comparison of Bayesian and classical approaches to inference on efficiency levels in stochastic frontier models with panel data. Journal of Productivity Analysis 14: 91-118.

Koop, G., and MFJ., Steel. 2001. Bayesian analysis of stochastic frontier models. In A Companion to Theoretical Econometrics. Baltagi B (ed.). Blackwell. Oxford.

Koop, G., J., Osiewalski, and M.F.J., Steel. 1994. Bayesian Efficiency Analysis with a Flexible Form: The AIM Cost Function. Journal of Business & Economic Statistics, American Statistical Association 12(3): 339-46.

Koop, G., M.F.J., Steel and J., Osiewalski. 1995. Posterior analysis of stochastic frontier models using Gibbs sampling. Computational Statistics 10 (4): 353–373.

Kozumi, H., and X., Zhang. 2005. Bayesian and Non-Bayesian Analysis of Gamma Stochastic Frontier Models by Markov Chain Monte Carlo Methods. Computational Statistics 20:575-593.

Kumbhakar, S. 1987. The specification of technical and allocative inefficiency in stochastic production and profit frontiers. Journal of Econometrics 34: 335–348.

Kumbhakar, S. 1990. Production frontiers, panel data, and time-varying technical inefficiency. Journal of Econometrics 46(1-2), pages 201-211.

Lee, Y.H., and P., Schmidt. 1993. A production frontier model with flexible temporal variation in technical efficiency. In: H.O. Fried, C.A.K. Lovell and S.S. Schmidt, Editors, The Measurement of Productive Efficiency Techniques and Applications. Oxford University Press.

MARM, 2008 Spanish Ministery for the Rural and Marine Environment. Annuario Estatistica para el Area.

Osiewalski, J., and M.F.J., Steel. 1998. Numerical tools for the Bayesian analysis of stochastic frontier models. Journal of Productivity Analysis 10: 103–117.

Schmidt, P., and R.C., Sickles. 1984. Production frontier and panel data . Journal of business and economic statistics 2(4): 367-374.

Tsionas, E. G. 2000. Full likelihood inference in normal-gamma stochastic frontier models. Journal of Productivity Analysis 13: 179–201.

Tsionas, E. G. 2002. Stochastic frontier models with random coefficients, Journal of Applied Econometrics 17 (2): 127–147.

Tsionas, E. G. 2006. Inference in dynamic stochastic frontier models. Journal of Applied Econometrics 21 (5): 669–676.

Van den Broeck, J., G., Koop, J., Osiewalski, and M.F.J., Steel. 1994. Stochastic frontier models : A Bayesian perspective. Journal of Econometrics 61(2): 273-303.