Technical efficiency and productivity analysis of Spanish citrus farms

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Jel classification: Q12, Q18, Q58

1. Introduction

The world citrus production has experienced continuous growth in the last decades. Almost all of the increase can be attributed to Brazil, the United States, and the Mediterranean region, and is mainly due to the expansion of acreage in citrus groves as a result of changes in consumer preferences in favour of healthier food. The annual average world citrus production during the period 2000-2007 is estimated at 109 million tons (FAO, 2009). Citrus is a significant fruit crop in international trade with more than 14 million tons exported in 2005 (FAO, 2009). The European Union (EU) is an active trader in the world market. It is the main destination as well as the main supply region with almost half of the world's imports and more than 40% of world exports

in 2005 (FAO, 2009). The Mediterranean region plays a prominent role as a world's fresh citrus exporter, providing nearly 60% of global fresh citrus fruit exports. Among the Mediterranean countries, Spain is the leading producer with more than 5 million tons, generating 52.6% of the EU pro-

Abstract

Spain occupies the first position in the European and Mediterranean rankings of citrus production and trade. Given the relevance of this sector, the main purpose of this study is to analyze its technical efficiency (TE) using the stochastic frontier model (SF) and decompose its productivity growth into various components using primal approach. We use a farm-level data for a sample of farms specialized in orange production.

Results indicate that Spanish citrus farms improved their efficiency during the period studied at a rate of 9.5%, (the estimated average efficiency level for our sample is 64.11%); they also show evidence in favour of an increase in total factor productivity at a rate of 2.7% per year. Allocation efficiencies, technical efficiency change, and scale effects were found to be the main factors that caused this growth in TFP.

Key words: Citrus, technical efficiency, total factor productivity

Résumé

L'Espagne occupe la première position à l'échelle européenne et méditerranéenne pour la production et la commercialisation des agrumes. Compte tenu de l'importance de ce secteur, nous en avons analysé, dans un premier temps, l'efficience technique (ET) en utilisant le modèle de frontière de production stochastique. Ensuite, nous avons décomposé l'augmentation de la productivité en appliquant l'approche primale. L'échantillon retenu dans cette étude est représenté par des exploitations agrumicoles spécialisées dans la production d'oranges.

Les résultats indiquent que les exploitations agrumicoles espagnoles ont amélioré leur efficience technique dans la période analysée, avec un taux de croissance de 9,5% (l'efficience moyenne de notre échantillon étant de l'ordre de 64,11%). Par ailleurs, nous constatons une augmentation de la productivité totale des facteurs avec un taux de croissance de 2,7% par an. L'efficience allocative, la variation de l'efficience technique et les effets d'échelle s'avèrent être les principaux facteurs qui déterminent l'augmentation de la PTF.

Mots clés: Agrumes, Efficience technique, productivité totale des facteurs.

duction and 4.9% worldwide production in 2007 (FAO, 2009). It is also the leading exporting country with almost 29% of total world exports in 2005 (FAO, 2009). Oranges are the main citrus fruit produced in Spain, representing 43.4% of the EU production and 4.2% of worldwide production in 2007 (FAO, 2009). Moreover, in 2006 Spain exported 40% of the oranges produced in its territory (MAPA, 2008) which represents 30.6% of the oranges exported in the world (FAO, 2009).

Given the relevance of this sector in Spain, the main purpose of this study is to analyze the technical efficiency and to decompose productivity growth into its different components for a sample of Spanish citrus farms. The main motivation underlying efficiency and productivity s-

tudies is the need to investigate and understand the forces that drive agricultural production growth in order to analyse and formulate any desired agricultural policy. It matters not whether future agricultural policy is concerned with promoting a sustainable or a more intensive agricultural production. In either case, the study of individual farm efficiency is essential in order to maximise the benefits hoped for from any policy. Technical efficiency affects farm's economic survival, the size distribution of farms, technological adoption and innovation and the overall input use in the agricultural sector. It is definitely worth the trouble to study agricultural efficiency, though surprisingly it is an agribusiness tool that has been neglected in the Spanish citrus sector¹.

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¹ Most studies on the efficiency of Spanish farms are focused on the milk sector (e.g. Álvarez and Arias, 2003). To our knowledge, no previous paper has focused on the efficiency of the Spanish citrus sector.

2. Materials and methods

Following Farrell (1957), the measurement of efficiency is based on the idea of comparing the actual firm performance with that of other similar firms belonging to the same sector or industry. A technique commonly used to measure a firm's technical efficiency is the stochastic frontier methodology (for a recent application of this method see Bozoglu and Ceyhan, 2007, Lambarraa et *al.*, 2007 and 2009). First introduced by Aigner *et al.* (1977), and Meeusen and Van den Broeck (1977), this method addresses the shortcomings of the deterministic approach by distinguishing between inefficiency and exogenous shocks that are outside the firm's control. A stochastic frontier production function can be expressed as follows:

$$y_{it} = f(x_{it}, t; \beta) e^{v_{it} - u_{it}}$$
 (1)

where y_{it} is the output of the i-th firm (i = 1,..., N) in period $(t = 1,..., T, f(x_{it}, t; \beta))$, represents the production technology, e is the exponential function, x_{it} is a $(1 \times K)$ vector of inputs and other factors influencing production associated with the i-th firm in period t, and β is a $((K + 1) \times 1)$ vector of unknown parameters to be estimated.

Following the standard literature (e.g. Aigner *et al.* (1977), and Meeusen and Van den Broeck (1977)), the disturbance term is composed of two parts: v_u which is a symmetric component that permits random variations of the frontier across firms, captures the effects of statistical noise outside the firm's control, and is assumed to be independent and identically distributed N $(0,\sigma_v^2)$. The second error term, u_u , is a one-sided, non-negative component associated with output-oriented technical inefficiencies and assumed to be distributed as truncated normal N⁺(m, σ_u^2). It is further assumed that the distributions of the two error terms are independent. Because v_u is a standard error term, we focus on u_u to analyse inefficiency. Following the Battese and Coelli (1992) specification, the temporal pattern of technical inefficiency is used, which takes the form:

$$u_{it} = \left\{ \exp\left[-\xi \left(t - T\right)\right] \right\} u_i \tag{2}$$

where, as noted, u_i is a non-negative random variable assumed to account for technical inefficiency in production and ξ is a parameter to be estimated. If the parameter ξ is positive (negative), technical efficiency tends to improve (deteriorate) over time. If $\xi=0$, output-oriented technical efficiency is time-invariant. Maximum likelihood techniques are used for the estimation of the stochastic frontier model. Variance parameters of the likelihood function $\tilde{\alpha}$ are estimated in terms of δ^2 and $\tilde{\alpha}$, where $\delta^2=\delta_v^2+\delta_u^2$ and $\tilde{\alpha}=\delta_u^2/\delta^2$ which must lie between 0 and 1².

After estimating the model, we measure the Total Factor Productivity (TFP) change and determine its various components by using the primal approach by Kumbhakar and Lovell (2000). Output growth is attributed to four main components: returns to scale, technical change, change in technical efficiency and allocative efficiency. TFP can be expressed as follows:

$$TFP = T\Delta + (\varepsilon - 1) \sum_{k} \left(\frac{\varepsilon_{k}}{\varepsilon}\right) x_{k}^{\infty} + \sum_{k} \left[\left(\frac{\varepsilon_{k}}{\varepsilon}\right) - S_{k}\right] x_{k}^{\infty} + TE\Delta$$
 (3)

Where a dot over a variable indicates its rate of change,

and TFP represents total factor productivity change. The expression $T\Delta = \frac{\partial f(x_{it}, t; \beta)}{\partial t}$ is a measure of the rate of technical change that captures changes in the maximum attainable output over time. An upward (neutral) [downward] movement of the production frontier will be represented by $T\Delta > (=)$ [<]0. The second component, $(\varepsilon - 1)\sum_{k} (\frac{\varepsilon_{\kappa}}{\varepsilon})^{\infty} x_{k}$, mea-

sures the contribution of scale economies to TFP changes, being $\varepsilon_k = \varepsilon_k(x_{it}, t; \beta) = \frac{x_k \left(\partial f(x_{it}, t; \beta) / \partial x_k \right)}{f(x_{it}, t; \beta)}$ the output elasticity

with respect to input x_k and $\varepsilon = \varepsilon(x_u, t; \beta) = \sum_k \varepsilon_k(x_u, t; \beta)$ a

measure of a firm's returns-to-scale. The expression $\sum_{k} (\frac{\mathcal{E}_{K}}{\varepsilon}) x_{k}^{\circ} > (=)[<]0$ indicates increases (constancy) [decreases] in input use. $T\hat{F}P$ will be increased if production is characterized by increasing (decreasing) returns to scale and there is an expansion (contraction) in input use. The third summand measures allocative inefficiency, or the deviation of input prices from the value of their marginal products and can be expressed as $\sum_{k=1}^{\infty} (\frac{\mathcal{E}_{k}}{\varepsilon}) - S_{k} x_{k}^{\circ}$, where

 $S_k = \frac{w_k x_k}{E}$ is a measure of the expenditure share of input k,

 w_k is the unit price of input k and $E = \sum_k w_k x_k$ is total ex-

penditure in inputs. Finally, $TE\Delta = -\frac{\partial u_n}{\partial t}$ is the primal measure of the rate of change in technical efficiency, that is, the gap between the production frontier and a firm's actual production.

3. Empirical implementation

To analyze the efficiency and productivity of Spanish farms, we use farm-level data from the Farm Accounting Data Network (FADN, 2009), for the period 1995-2003. Our sample is composed of 859 observations of citrus farms specialising in orange production.

FADN consists of an annual survey carried out by the member states of the EU. It provides representative data of EU agricultural holdings along three dimensions: region, economic size and type of farming. Since FADN farms producing oranges are aggregated into a broader group (citrus

² The variance parameter g evaluates the relevance of technical inefficiency in explaining output variability among Spanish citrus farms (e.g. Battese et al., 1997 and Coelli et al., 1998).

fruits), a sample of farms specialized in orange production is chosen by including those farms whose orange sales represent more than 70% of their citrus sales (in all selected cases, acreage in orange groves represents more than 50% of total citrus area). We have also taken data from the Spanish Ministry of Agriculture and from Eurostat (2009), since the market price variables required to carry out the Total Factor Productivity growth decomposition are not available in the FADN dataset. Therefore, to define the pesticide, fertilizer and other variable input prices as well as the output price index, we use national price indices taken from Eurostat. The Spanish Ministry of Agriculture provided land prices at the national level. Labour prices are approximated at the farm level by dividing a farm's labour expenses by the hours of labour.

The production frontier function, which is specified as a Cobb-Douglas with no neutral technical change, takes the form:

$$y_{it} = \beta_0 e^{\beta_t t} \prod_{k=1}^K x_{it}^{(\beta_k + \beta_{kt} t)} e^{\nu_{it} - u_{it}}$$
(4)

Production,, is defined as an implicit quantity index by dividing total orange sales in currency units by the orange price index. Vector x_{ii} is defined as a (1×4) vector that contains four inputs. The first input, x_1 , includes both fertilizers and pesticides, x_2 comprises variable crop-specific inputs other than fertilizers and pesticides, x_3 represents the hectares occupied by orange groves and x_4 represents labour input and is measured in man hours per year. Input use variables x_1 and x_2 are expressed as implicit quantity indices by dividing the consumption of these inputs in currency units by their respective price indices. All variables in the stochastic frontier are normalized³ with respect to their own mean and expressed in logs in the estimation process. The parameters of the stochastic production frontier model are estimated by using the maximum likelihood method.

Several hypotheses can be tested by using the generalized likelihood-ratio statistic, $\lambda = -2$ {1n $L(H_0) - 1$ n $L(H_1)$ }, where $L(H_0)$ and $L(H_1)$ denote the values of the likelihood function under the null (H_0) and the alternative (H_1) hypothesis, respectively. The tested hypotheses are described in the following lines. First, if $\gamma = \mu = \xi = 0^4$ then the technical inefficiency effects are non-stochastic and equation (1) reduces to an average response function. Second, if $\mu = \xi = 0$ then the technical inefficiency is time-invariant given the stochastic frontier model. Third, if $\mu = 0$ then the stochastic frontier model has a time-varying output-oriented technical efficiency and the inefficiency effects have a half-normal distribution. Fourth, if $\xi = 0$ then there is a time-invariant output-oriented technical efficiency. Fifth, if $\sum_k \beta_k = 1$ and $\sum_k \beta_{kT} = 0$, we have constant returns to scale. Sixth, and

finally, if $\sum_{k} \beta_{k} = 1$ and $\sum_{k} \beta_{kT} = \forall k$ and $\beta_{T} = \beta_{TT} = \beta_{kT} = 0$ $\forall k$, we get Hicks-neutral and zero technical change respectively (Karagiannis and Tzouvelekas, 2004).

4. Results and discussion

Table 1 presents summary statistics for the variables used in the analysis. From this table it can be appreciated that our sample farms' average annual output is around 16,613 euro/year. These farms cultivate, on average, 4.43 hectares, employ 1,848 labour hours per year, and spend 2,789 euro/year on pesticides and fertilizers, and 1,674 euro/year on other crop-specific costs.

Table 1 - Description of the sample data (N=859). Variables used in the analysis Variable Minimum Maximum Euro/year 34558 Pesticides Fertilizers Euro/year 1,674 1,164 0.00 9,417 crop-specific hours/vea 1,848 15,108 Labour 1.16 ha/year Land 14,075 197,158 21.97

Tables 2, 3, 4 and 5 present the results derived from estimating the stochastic frontier model, output elasticities, technical efficiency scores, and model specification tests, respectively.

Table 2 - Maximum Likelihood Estimates of a Cobb-Douglas Production Frontier Function for citrus farms in Spain, 1995-2003.

Parameter	Estimate	Standard Error		
β_{o}	0.60	0.03*		
$eta_{\!\scriptscriptstyle K}$	0.32	0.07*		
$oldsymbol{eta_{ t L}}$	0.18	0.03*		
$eta_{\scriptscriptstyle F}$	0.22	0.03*		
eta_{oc}	0.10	0.02*		
$oldsymbol{eta}_{ extit{ iny KT}}$	-0.05	0.06		
$eta_{\!\scriptscriptstyle LT}$	0.13	0.03*		
$eta_{\!\scriptscriptstyle FT}$	0.06	0.03*		
$eta_{\scriptscriptstyle OCT}$	-0.006	0.03		
$oldsymbol{eta}_T$	-0.26	0.04*		
$oldsymbol{eta}_{TT}$	-0.23	0.03*		
σ_{u}^{2}	3.29	0.52*		
γ	0.96	0.006*		
ξ	0.02	0.008*		

Note: L refers to labour, K to Land, F to Fertilizers and OC to other crop-specific costs.

First-order parameters (Table 2), β_k , are all positive and statistically significant thus indicating that production is increasing in all inputs: pesticides and fertilizers, other cropspecific variable inputs, land and labour. The variance parameter, γ , is statistically significant and relatively close to one, which suggests that technical inefficiencies are rele-

³ Specifically, the following transformation is used: $x' = \ln(x/\bar{x})$ where \bar{x} is the sample mean of x.

⁴ As we assumed above, technical inefficiencies are distributed as $N+(m,\sigma_u^2)$.

^{*} Indicates that the parameter is significant at 5% significance level.

Table 3 - Output Elasticities for Spanish citrus farms, 1995-2003.

•			•						
	1995	1996	1997	1998	1999	2000	2001	2002	2003
Output Elasticities									
Land	0.41	0.37	0.35	0.33	0.32	0.31	0.30	0.29	0.28
Labour	-0.02	0.06	0.12	0.15	0.18	0.21	0.23	0.24	0.26
Fertilizers & pesticides	0.12	0.16	0.19	0.20	0.22	0.23	0.24	0.25	0.25
Other crop-specific costs	0.11	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
Returns to Scale	0.63	0.72	0.77	0.80	0.83	0.85	0.87	0.89	0.91

vant in explaining output variability among citrus farms. It also suggests that one should not rely solely on the average production function response as an adequate representation of the sample data. The parameter ξ captures the temporal variation of individual output-oriented technical efficiency. It is positive and statically significant, thus indicating that technical efficiency improves over time.

Results also suggest that while there is an increase in labour and fertilizer and pesticide productivity over time, land productivity diminishes (Table 3). This latter result may be due to the relevance of extensive production methods and offers scope for future improvements through the use of better practices and techniques. Table 3 provides evidence that citrus production is characterized by decreasing returns-to-scale⁵ (the scale elasticity's average is on the order of 0.81 during the period 1995-2003). Since, in the presence of decreasing returns to scale, changes in production are proportionally less than proportional changes in inputs, this makes an increase in the farm size unattractive.

Table 4 - Model Specification Tests for citrus farms. Hypothesis LR test-statistic Critical Value $(p \le 0.05)$ Average Production Function, i.e., γ=u=ξ=0 $\chi_3^2 = 7.81$ 950.54 Aigner et al., (1977) SPF model with time-invariant output-32.53 $\chi_2^2 = 5.99$ oriented technical efficiency, i.e., $\mu=\xi=0$ Aigner et al., (1977) SPF model with time-varying output- $\chi_1^2 = 3.84$ 22.61 oriented technical efficiency, i.e., µ=0 Time-invariant output-oriented technical efficiency, i.e., $\xi = 0$ 10.18 $\chi_1^2 = 3.84$ Constant returns-to-scale, i.e., $\sum_{k} \beta_{k} = 1$ and $\sum_{k} \beta_{kT} = 0$ $\chi_5^2 = 11.1$ 12.84 Hicks-neutral technical change, i.e., $\beta_{kT} = 0 \ \forall k$ $\chi_4^2 = 9.49$ 12.55 Zero technical change, i.e., $\beta_T = \beta_{TT} = \beta_{kT} = 0 \ \forall k$ 64.17 $\chi_6^2 = 12.6$

As explained above, we use the generalized likelihood-ratio statistic to test for the null hypothesis that inefficiency effects are absent from the model, that is, $\gamma = \mu = \xi = 0$ (see table 4). The null hypothesis is rejected at 5% significance level, confirming that Spanish orange growers suffer from technical inefficiencies. The null hypothesis that technical inefficiency is time-invariant given the stochastic production frontier model ($\mu = \xi = 0$) is also rejected at 5% significance level. The third hypothesis tested, that of the stochastic frontier model with time-varying output-oriented techni-

Table 5 - Measures of Technical Efficiency for Spanish citrus farms, 1995-2003.

1995	1996	1997	1998	1999	2000	2001	2002	2003
4	8	10	7	7	7	5	8	5
2	7	7	3	5	7	4	2	1
10	9	8	5	6	1	3	4	4
3	13	10	9	8	7	8	6	6
15	12	13	9	7	8	9	9	8
10	12	10	11	12	10	7	6	6
16	16	17	16	15	15	14	15	13
23	28	29	29	32	32	32	32	32
4	6	6	5	7	7	8	7	6
63%	60%	60%	64%	64%	64%	67%	66%	69%
	4 2 10 3 15 10 16 23 4	4 8 2 7 10 9 3 13 15 12 10 12 16 16 23 28 4 6	4 8 10 2 7 7 10 9 8 3 13 10 15 12 13 10 12 10 16 16 17 23 28 29 4 6 6	4 8 10 7 2 7 7 3 10 9 8 5 3 13 10 9 15 12 13 9 10 12 10 11 16 16 17 16 23 28 29 29 4 6 6 5	4 8 10 7 7 2 7 7 3 5 10 9 8 5 6 3 13 10 9 8 15 12 13 9 7 10 12 10 11 12 16 16 17 16 15 23 28 29 29 32 4 6 6 5 7	4 8 10 7 7 7 2 7 7 3 5 7 10 9 8 5 6 1 3 13 10 9 8 7 15 12 13 9 7 8 10 12 10 11 12 10 16 16 17 16 15 15 23 28 29 29 32 32 4 6 6 5 7 7	4 8 10 7 7 7 5 2 7 7 3 5 7 4 10 9 8 5 6 1 3 3 13 10 9 8 7 8 15 12 13 9 7 8 9 10 12 10 11 12 10 7 16 16 17 16 15 15 14 23 28 29 29 32 32 32 4 6 6 5 7 7 8	4 8 10 7 7 7 5 8 2 7 7 3 5 7 4 2 10 9 8 5 6 1 3 4 3 13 10 9 8 7 8 6 15 12 13 9 7 8 9 9 10 12 10 11 12 10 7 6 16 16 17 16 15 15 14 15 23 28 29 29 32 32 32 32 4 6 6 5 7 7 8 7

cal efficiency whose inefficiency effects have a half-normal distribution (μ =0) is also rejected at 5% significance level. The fourth hypothesis tested (ξ =0) reveals that output-oriented technical efficiency is time variant. The hypothesis of the presence of constant returns-to-scale ($\Sigma_k \beta_k = 1$ and $\Sigma_k \beta_{kT} = 0$) is rejected at 5% significance level, which confirms the presence of decreasing returns-to-scale. Both the sixth and the last null hypotheses are rejected implying the existence of non-neutral technical progress and non-zero technical change within the Spanish orange sector, given the specified production model.

Predicted technical efficiencies take an average value of 64.11% for the period studied for Spanish orange farms (Table 5). The distribution of efficiency scores by farms shows that a majority of farmers (74% of the sample) have efficiency scores above 60%. These sub-100% efficiency levels suggest that production, on average, could further increase through a more efficient use of inputs in the sector. The evolution of technical efficiencies during the period of study shows an efficiency improvement for orange growers that increases from 63% in 1995 to 69% in 2003. Moreover, we state a positive evolution among years for farms having technical efficiency scores greater than 80% which passes from 30% to 46% in the last year. This movement of farms to superior efficiency scores interval is confirmed by the positive value of parameter ξ that indicates that technical efficiency tends to improve over time. The tendency of the technical efficiency to improve during the period studied

Table 6 - Decomposition of Output Growth for Spanish orange farms (average values for the 1996-2003 period).

	TFP	TEC	SC	AE	TC
1996	0.024	0.005	-0.007	0.027	0.00001
1997	0.145	0.002	0.021	0.121	-0.00007
1998	0.092	0.004	-0.035	0.124	-0.00010
1999	0.025	0.001	0.030	-0.006	-0.00013
2000	0.075	0.005	-0.015	0.085	-0.00018
2001	-0.031	0.001	0.018	-0.050	-0.00022
2002	-0.146	0.002	0.008	-0.158	-0.00025
2003	0.036	0.002	-0.011	0.046	-0.00028
Average	0.027	0.003	0.001	0.02	-0.0001

Note: TFP refers to Total Factor Productivity, SC to Scale component, TC to technical change, TE to: Technical Efficiency Change and AE to Allocative Efficiency.

⁵ The scale elasticity is inferior to one throughout the period 1995-2003, which is an indicator of decreasing returns to scale.

suggests that Spanish growers have improved the use of inputs in the orange sector.

Results of the TFP growth decomposition are reported in Table 6. As noted above, increases in TFP can be decomposed into its technical, scale, technical efficiency and allocative inefficiency components. Results show an increase on the order of 2.7% in productivity during the period of analysis. Technical change has had a negligible negative impact. Allocative efficiency is the most important component in productivity growth (2.3%) and is followed, at a distance, by both the technical efficiency change (0.318%) and the scale components (0.1%).

The evolution during the period studied shows that technical efficiency experienced particularly strong improvements during 1996 and 2000. The positive sign of this component suggests that the gap between the production frontier and citrus farms' actual production was reduced throughout the period of analysis. The varying sign of the scale component suggests that farmers do not always increase (decrease) farms' size where economies (diseconomies) of scale are present and that indeed they sometimes choose production strategies that do not account for economies of scale⁶. Allocative efficiency fluctuated during the period, which implies that the Spanish citrus farms either take advantage or waste the opportunity that follows a deviation in input prices from the value of their marginal product. And finally, technical change suffered a negligible decline over time.

5. Conclusion

Our analysis of the technical efficiencies and factor productivity changes of Spanish orange growers was built upon an estimated stochastic frontier model. Productivity growth was decomposed into four key components. An important finding is that Spanish orange production is characterized by decreasing returns to scale. With respect to farm size, bigger is not better.

The estimated average efficiency level for our sample and throughout the period studied is 64.11%. Spanish orange growers have improved their technical efficiency scores from 63% in 1995 to 69% in 2003. Results show an increase in TFP in the Spanish orange sector at a rate of 2.7% per year for the period studied. Increases in production have been achieved through improvements in technical efficiency change, allocative efficiency and better use of economies of scale. However, technical change has had a negative, though negligible impact and confirms the negative effect of the time trend in the production frontier.

Further research will be needed to determine the causes of the downward movements in the production frontier. We suggest two possible lines of research. First, one should analyze to what extent a significant decrease in orange prices during the second half of the 1990s may have discouraged investments during this period of time. Second, there has been a decline in orange consumption in all developed countries as a result of substitution, since improvements in transportation and storage have favoured a wider and longer availability of competing fruits. It would thus be interesting to assess whether this decline in consumption has influenced on the orange sector investment demand.

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7. References

Aigner D.J., Lovell C.A.K., and Schmidt P.J., 1977, Formulation and Estimation of Stochastic Frontier Production Function Models, Journal of Econometric, 6, 21-37.

Battese G.E., and Coelli T.J., 1992, Frontier production functions, technical efficiency and panel data: With application to paddy farmers in India, Journal of Productivity Analysis, 3, 153-69.

Bozoglu M., and Ceyhan V., 2007, Measuring the technical efficiency and exploring the inefficiency determinants of vegetable farms in Samsun province. Agricultural Systems, 94, 649-656.

EUROSTAT, 2009, Agriculture Dataset. Available at http://epp.eurostat.cec.eu.int.

FADN, 2009 (Farm Accounting Data Network). Available at http://ec.europa.eu/agriculture/rica/dwh/index en.cfm.

FAO, 2009, FAODATA Dataset. Available at http://www.fao.org/.

Farrell M.J., 1957, *The Measurement of Productive Efficiency*, Journal of the Royal Statistical Society, Series A 120, 53-81.

Karagiannis G., and Tzouvelekas V., 2004. *Explaining output growth with a heteroscedastic non-neutral production frontier: the case of sheep farms in Greece*, European Review of Agricultural Economics, 32 (1), 51–74.

Kumbhakar S.C., and Lovell C.A.K., 2000. *Stochastic Frontier Analysis*, Cambridge University Press, New York, 344 p.

Lambarraa F., S.E. Stefanou, T. Serra, and J.M. Gil. 2009. The impact of CAP reform on the Spanish COP sector, Ag. Eco. 40: 355-364

Lambarraa F., Serra T., and Gil. J.M., 2007, *Technical efficiency and decomposition of productivity growth of Spanish olive farms*, Spanish Journal of Agricultural Research, 5 (3), 259-270.

MAPA, 2008, Anuario de Estadística Agroalimentaria. Available at http://www.mapa.es/es/estadistica/pags/anuario/2007/ indice.asp.

Meeusen W., and Van den Broeck J., 1977 Efficiency estimation from Cobb-Douglas production functions with composed error, International Economic Review, 18, 435-444.