Efficiency and technology of dairy sheep production systems in Castilla-La Mancha, Spain. A metafrontier approach

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DOI: 10.30682/nm2201c
JEL codes: C61, M11, Q12

Abstract

This paper deals with the efficiency level of cereal-dairy sheep production systems in the Mediterranean Basin. It studies them in the Protected Designation of Origin "Manchego Cheese", located in Castilla-La Mancha (Spain). Previous studies have alerted to the low productivity levels in these farms, suggesting conducting an efficiency analysis. This work evaluates technological levels by means of synthetic indexes. Two different groups were defined. Technical efficiency was estimated using Data Envelopment Analysis with metafrontier models. The higher the technological level, the higher the efficiency level. Low technology farms could increase their production at least around 23% using the technologies of the high-technology group. Thus, it could be wise to apply new technologies, as new feeding techniques, and the use of troughs of cement, dungheaps, flushing and selective breeding. Increase farm size is a way to implement these technologies. Special attention to managerial functions, mainly organisation and planning, is also advisable. The government must improve the agricultural policies. These actions could increase efficiency, resiliency and sustainability of the farms.

Keywords: *Dairy sheep production systems, Data envelopment analysis, Efficiency, Management, Metafrontier.*

1. Introduction

There are approximately 2,200 million sheep and goats in the world. The 20.8% aim for dairy production, producing about 3.5% of the world's milk. The population size of sheep and goats in the European Union (EU) is approximately 74 million heads, of which sheep represent round about 83%. Three quarters of these sheep live in Spain (24.8%), Romania (16.6%), Greece (13.5%), France (11.4%) and Italy (11.2%) (Eurostat, 2020). Four countries – France, Greece, Italy, and Spain – lead the international markets in sheep and goat dairy products. The productive models of these countries have also characteristic features. In general, they are based on the use of specific breeds and Protected Designation of Origin (PDO)

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cheeses, which are usually produced following traditional recipes.

The dairy sheep-cereal production systems are multifunctional and have a crucial historical, economic and social importance (Arzubi *et al.*, 2009; Vagnoni *et al*., 2018). Nevertheless, Mediterranean dairy sheep production farms have limits to their productivity, like weather and land conditions (de Rancourt *et al.*, 2006; Rivas *et al.*, 2014; Morantes *et al*., 2017).

According to national census (MAPA, 2019), there are 15.5 x 10^6 millions of sheep in Spain, and Castilla-La Mancha has the 15.11% of this amount. The most frequent production systems are concerned with the autochthonous breed called "Manchega" breed.

The observed tendency of the farms to disappear from Europe is an important fact in the dairy sheep production economic sector in Spain. Many farmers left their production systems due to low productivity levels obtained from the herds (Ripoll-Bosch *et al.*, 2012). Morantes *et al.* (2014) studied the socio-economic characteristics of these production systems. These authors, and García-Díaz *et al.* (2012), indicated that agriculture and livestock farms maintenance requires an increase in profitability.

In other previous research, Morantes *et al.* (2017) dealt with the importance of management in dairy sheep production systems in Castilla-La Mancha. They designed and created four indexes of the management functions: planning, organisation, management and control. The results showed that the managerial levels were not optimal, and proved that the productivity levels were low. The conclusions proposed performing an in-depth study on the farms efficiency level, to reach a general improvement of all the processes.

As it is well known, technical efficiency and technological level are productivity determinant factors. The firms' technological level is important for their efficiency analysis. Kompas and Che (2006) have studied the technical efficiency on Australian dairy farms and its relation with the technology. Mukherjee *et al.* (2012) estimated the dairy farms' technical efficiency in Florida and Georgia, with a stochastic frontier analysis considering the technological level as external factors in the production frontier.

One of the main objectives of this paper is to conduct an efficiency analysis of the dairy sheep production systems in Castilla-La Mancha. To do it, we first estimated the firms' efficiency level applying Data Envelopment Analysis (DEA) techniques. Then Truncated Regression analysis was also applied, in order to detect the influential variables on the farm efficiency levels. However, this methodology requires the sample to be homogeneous in technology. For this reason, we previously analysed the dairy-sheep-production-system technological level.

There are management techniques that require substantial investment for a long time. The present paper assesses farm technological levels depending on these implemented technologies and the productivity levels in a long-term period, and performs a long-term technological index. The firms are classified into two groups according to their different technologies. This fact can originate different production frontiers. These groups have diverse technologies, then suitable approaches for the efficiency analysis are required, and two production frontiers should be taken into account. The appropriate methodology is called Metafrontier Production Function (Battese *et al.*, 2004; O'Donnell *et al.*, 2008; Latruffe *et al.*, 2012; Ozden and Dios-Palomares, 2016; Melo-Becerra and Orozco-Gallo, 2017).

On the other hand, the knowledge of the relevant factors to the technical efficiency levels is crucial. These factors relate to the short-term technologies and the management practices.

There are management technologies implemented in a short time term. Thus, they could be easily modified to improve results, if necessary. These techniques, and several aspects of the management functions, could be determinants for the technical efficiency (Urdaneta *et al.*, 2013). In the present paper, a short-term technological index is also performed. This index resumes all these technologies.

The organisation and the control indexes, previously calculated by Morantes *et al.* (2017), has been also used as an explicative variable in the analysis.

In this paper, we used the same sample of Morantes *et al.* (2017), and we applied diverse approaches as survey, index calculation, multivariate analysis, DEA-metafrontier models, statistical tests, regression methods, bootstrap techniques, etc.

As a relevant added value, we evaluated the technological and efficiency levels. In addition, the main influential factors of both technological and efficiency levels were found.

The detection of these factors allows the decision-makers to perform improvement actions, to relieve the existing problems. It is important to achieve sustainability in these systems, which currently has originated changes in the type and intensity of land utilization, and led to environmental and landscape degradation (Rivas *et al.*, 2015).

All these findings enable us to offer advice on the strategies to implement, to improve the farm production systems, and the performance of the overall economic sector. Indeed, it will be able to extrapolate these advices and conclusions to other similar firms in the Mediterranean Basin.

2. Materials and methods

2.1. *Descriptive aspects*

This paper works with data, which come from our previous research (Morantes *et al.*, 2014; Rivas *et al.*, 2014; Morantes *et al.*, 2017). The study was conducted in the region of Castilla-La Mancha (Spain), characterised by a Mediterranean climate (Caballero, 2009).

These production systems are usually family-run. The majority of them are agriculture and livestock farms (mixed farms). These farms provide multiple products (milk, lamb, and cheese). They are mainly oriented to produce milk products as Manchego cheese. A detailed description of these farms can be seen in Rivas *et al.* (2014). The Protected Designation of Origin (PDO) "Manchego Cheese" consists of 869 farms located in the natural region called "La Mancha".

Table 1 - Stratified Random Sample.

Province	*Stratum*	*Sheep*	*Farms*	*Sample Size*
Albacete	I	(0, 366]	38	7
	II	(366, 1033]	58	10
	III	(1033, 1700]	24	5
	IV	(1700, 2366]	12	3
	Mean	958.32	*Total*	25
Ciudad Real	I	(0, 200]	56	10
	II	(200, 600]	260	44
	III	(600, 1000]	75	14
	IV	(1000, 1400]	20	4
	V	(1400, 1800]	11	3
	Mean	532.42	*Total*	75
Cuenca	I	(0, 244]	29	5
	II	(244, 688]	90	15
	III	(688, 1133]	33	6
	IV	(1133, 1577]	9	2
	Mean	617.89	*Total*	28
Toledo	I	(0, 133]	7	2
	II	(133, 466]	87	15
	III	(466, 800]	45	9
	IV	(800, 1133]	15	3
	Mean	499.71	*Total*	29
	Total Mean	609	869	157

A representative stratified random sample with proportional allocation was selected in accordance with two classification criteria (province and census) (Table 1).

The farms of each province were divided in strata according to the number of sheep of the farm. The number of strata of each province was selected following the Sturges rule taking into account the proportional allocation, and a random sample was selected from each stratum with sampling fraction of p = 0.15. The sample size was 130 farms. In addition, in order to guarantee a suitable effective sample size even in the cases where some instances of the sample must be removed from it, 27 extra farms were selected using the same sampling design. No instance removing was necessary. Thus, the final sample size was 157 (Table 1). The experimental error was 7.82% with a significant level of 5%. (Cochran, 1977).

A survey of 226 questions was designed, to get data from the farms regarding 12 relevant aspects: (1) situation and use of the land, (2) equipment, (3) livestock size, (4) labour (family members and employees), (5) feeding management, (6) grazing, (7) breeding management, (8) health management, (9) milking management and milk quality, (10) economic issues, (11) social issues, and (12) attributes of the management functions: planning, organisation, direction and control.

This research also deals with some results of Morantes *et al.* (2017) regarding the indexes of organisation and control. In that paper, the organisation index was built including several issues, like the manager's ownership, the organisational chart, and the personnel selection method. On the other hand, two aspects were considered for the control index: if the farmer provides records or not, and the evaluation of the objective. Table 2 collects descriptive values of both indexes.

Table 2 - Descriptive values for the organisation and control indexes.

Statistics	*Organisation index (OI)*	*Control index (CI)*
Total sample		
Valid data	138	138
Mean	0.50	0.53
Standard deviation	0.20	0.39
Minimum	0.19	0.00
Maximum	1	1
HTG Group		
Valid data	32	32
Mean	0.53	0.62
Standard deviation	0.22	0.39
Minimum	0.19	0.00
Maximum	0.88	1
LTG Group		
Valid data	106	106
Mean	0.50	0.50
Standard deviation	0.19	0.38
Minimum	0.19	0.00
Maximum	1	1

2.2. *Evaluation of the long and short term management strategies*

Two types of technological synthetic indexes were designed and made, in order to analyse the management strategies: long-term technological index (LTTI), and short-term technological index (STTI). The LTTI considers strategies where the techniques involved require plans of investment and revenue during several years (Table 3).

On the other hand, the STTI incorporates strategies, which could be easily modified or cancelled (Table 4).

Several methods to build synthetic indexes have been described in the literature. The common objective is to quantify some issue in a set of individuals or firms.

In this paper, we have applied the budget allocation process (BAP). All the management variables are dichotomous (the value belongs to the set {0, 1}), where the value 0 means absence and the value 1 means presence. A panel of experts was consulted in order to assign the weights to the variables in the synthetic indexes designed. This panel of specialists consists of 12 people: 7 vets, 3 agronomists and 2 farmers. Likert scale was applied (Likert, 1932; Cuervo, 2009), and the assessed values were: 1 for total disagree, 2 for disagree, 3 for indifference, 4 for agree, and 5 for total agree.

The formula for each technological index is the following:

$$I = w_1 MS_1 + w_2 MS_2 + \ldots + w_n MS_n = \sum_{i=1}^{n} w_i MS_i \quad (1)$$

where I is the index (LTTI or STTI), w_i is the weight assigned by the experts to the variable i-th included in the index, MS_i (Management Strategy) is the value of such dichotomous variable (0 or 1).

Table 3 - Weights of the variables that compose the long-term technological index (LTTI) and proportion of livestock farms where the strategy is developed in practice.

Management strategy	*Weights*	*Strategy developed in practice % (n)*		
		Total sample	*HTG Group*	*LTG Group*
Manage grazing lots by productive group	0.13	54.8 (86)	54.8 (23)	54.3 (63)
Uses genetic value as criterion for replacement of males	0.13	41.4 (65)	64.3 (27)	32.8 (38)
Uses genetic value as criterion for replacement of females	0.12	43.9 (69)	66.7 (28)	35.7 (41)
Has mechanical milking	0.12	86.0 (135)	92.9 (39)	82.8 (96)
Has cement screed	0.10	24.8 (39)	38.1 (16)	19.8 (23)
Has dung	0.10	29.3 (46)	45.2 (19)	23.5 (27)
Has silo	0.11	30.6 (48)	35.7 (15)	28.7 (33)
Has hayloft	0.10	29.9 (47)	35.7 (15)	27.8 (32)
Has feed belt	0.09	12.1 (19)	23.8 (10)	7.8 (9)

n: number of farms.

Table 4 - Weights of the variables that compose the short-term technological index (STTI) and proportion of livestock farms that develop the practices.

Variable	*Weights*	*Developed strategy % (n)*		
		Total sample	*HTG*	*LTG*
Has Unifeed	0.05	63.7 (100)	71.4 (30)	60.9 (70)
Manages lots of feed in the milking	0.06	38.9 (61)	54.8 (23)	33.0 (38)
Manages lambing season	0.06	82.8 (130)	90.5 (38)	80.0 (92)
Assisted copulation	0.05	29.9 (47)	57.1 (24)	20.0 (23)
Male effect	0.05	30.6 (48)	38.1 (16)	27.8 (32)
Flushing	0.05	14.6 (23)	19.0 (8)	13.0 (15)
Artificial insemination	0.03	36.3 (57)	61.9 (26)	27.0 (31)
Voluntary losses in female sheep	0.06	95.5 (150)	100.0 (42)	93.9 (108)
Voluntary losses in male sheep (ram)	0.05	93.0 (146)	90.5 (38)	93.9 (108)
Applies mastitis vaccine	0.03	24.8 (39)	33.3 (14)	21.7 (25)
Applies vaccine agalactia contagious	0.04	91.7 (144)	92.9 (39)	91.3 (105)
Applies intramammary drying treatment in ewes	0.05	47.1 (74)	50.0 (21)	46.1 (53)
Applies drying treatment to the whole flock	0.04	43.3 (68)	47.6 (20)	41.7 (48)
Vitamins and minerals applied to lambs	0.05	15.3 (24)	19.0 (8)	13.9 (16)
Has milk tank	0.03	96.8 (152)	100.0 (42)	95.7 (110)
Milking parlor with low line	0.05	45.9 (72)	38.1 (16)	48.7 (56)
Use water cleaner	0.04	42.7 (67)	57.1 (24)	37.4 (43)
Has vacuum valve	0.05	73.9 (116)	85.7 (36)	69.6 (80)
Has electricity	0.05	96.2 (151)	97.6 (41)	95.7 (110)
Division of stockyards by production lots	0.06	86.6 (136)	95.2 (40)	83.5 (96)
Has area of lambing	0.05	84.7 (133)	92.9 (39)	81.7 (94)

n: number of farms.

2.3. *Technical efficiency: analysis and determinants*

The technological heterogeneity was studied using factorial and cluster analyses. They were performed based on the variables, which are determinants of the different technological levels. These variables were the LTTI, and the following productivity indicators: Milk/E (Litre/Ewe), IMS/E (€/Ewe) (Income from Milk Sales / Ewe), TSI/E (€/Ewe) (Total Sales Income / Ewe), GM/E (€/E) (Gross Margin / Ewe), L/UAW (Litres of Milk / Unit of Agricultural Work), IMS/UAW (€/UAW) (Income of Milk Sales / Unit of Agricultural Work), TSI/UAW (€/UAW) (Total Sales Income / Unit of Agricultural Work), GM/UAW (€/UAW) (Gross Margin / Unit of Agricultural Work), L/ha (Litres / hectare), IMS/ha (€/ha) (Income Milk Sales / hectare), and GM/ha (€/ha) (Gross Margin / hectare). A factorial analysis with all the variables was performed in order to detect the factors with a high impact on the sample total variance. Then, a cluster analysis with the found factors was applied with the K-means methodology. The significant difference among groups was tested for each variable (t-Student because there are two groups).

Previously to the efficiency analysis, a statistic method to detect atypical values (outliers) was applied.

The TE (Technical Efficiency) analysis was performed with one output: milk production (litres); and five inputs: ewes (number), land (ha), labour (units of agricultural work) (UAW), fixed capital (€) (revenues from buildings, facilities, equipment, and animals), working capital (€) (feeding costs, National Insurance payments, health costs, interest from capital).

Data Envelopment Analysis is a powerful way for the technical efficiency analysis, and determines the efficient firms. These firms make optimal use of the resources for the production of outputs (milk in this case) (Cooper *et al.*, 2007). This methodology has been applied by many studies to diverse sectors (Dios-Palomares *et al.*, 2020).

The estimation of a firm's efficiency is defined by its distance to the production frontier. However, all the firms taken in consideration to estimate the frontier must use the same technology for fair comparison.

In our case, to estimate efficiency, the Data Envelopment Analysis (DEA) methodology was applied with a metafrontier approach (Coelli, 1995; O'Donnell *et al.*, 2008; Ozden and Dios-Palomares, 2016), and dealing with two frontiers corresponding to the two technological groups considered. This metafrontier methodology implies, in our analysis, the estimation of three production frontiers, as will be seen below.

The DEA methodology is applied to each frontier and consists of calculating, by mathematical programming, the distance from each point (firm) to the envelope formed by all the others. It is necessary to solve the DEA model for each company in the sample. (Cooper *et al.*, 2007).

The formulation of the DEA mathematical model starts with the definition of the *n* decision making units (DMU) under study. The *j*-th DMU is denoted by DMU_j with $j = 1, \ldots, n$. DMU_j uses *m* inputs (indexed $i = 1, \ldots, m$) to produce *s* outputs (indexed $r = 1, \ldots, s$). The production possibility set will be estimated on the basis of the sample values of *n* DMUs. Thus, if $x_j \in \mathrm{R}_+^m$ is the vector of inputs of DMU_j, and $y_j \in \mathrm{R}_+^s$ is its vector of outputs, for every $j = 1, \ldots, n$, then the problem data are characterised by the matrix of inputs $X = (x_j) \in \mathrm{R}_+^{m \times n}$, and the matrix of outputs $Y = (y_j) \in \mathrm{R}_+^{s \times n}$. For each fixed DMU_o (with *o* varying $o = 1, \ldots, n$) the output-oriented BCC model envelopment form (Banker *et al.*, 1984), is written in the way:

$$\max_{\eta,\lambda} \eta \tag{2}$$

subject to

$$X\lambda \leq x_o \tag{3}$$

$$\eta y_o - Y\lambda \leq 0 \tag{4}$$

$$e\lambda = 1 \tag{5}$$

$$\lambda \geq 0 \tag{6}$$

where the scalar η measures the efficiency related to the DMU_o, λ is a column vector ($n\times1$) which weighs the sample DMUs, and the constraint $e\lambda = 1$ means $\sum_{j=1}^{n} \lambda_j = 1$ and characterises variable return of scale models.

Firstly, pure efficiency (BCC-efficiency) was estimated with this BCC model. Then, technical efficiency (CCR-efficiency) was estimated with a CCR model with constant returns to scale (Charnes *et al.*, 1978). In this CCR model, the constraint $e\lambda = 1$, i.e., $\sum_{j=1}^{n} \lambda_j = 1$, is omitted. Then, scale efficiency (SE) was computed as the ratio between pure and technical efficiencies.

The metafrontier concept, developed by O'Donnell *et al.* (2008), was applied. This model considers that technical efficiencies, related to farms with different technologies, are not comparable under the same production frontier. Figure 1 shows a methodological simplification with two inputs (X1 and X2) and one output (Y). The frontiers associated to the two technological groups (HTG – High Technological Group – and LTG – Low Technological Group –) were estimated separately. The intra-group efficiency $TE_{j_k}^{k}$, with K groups, n_k units (DMUs) in each group k, and $k = 1, \ldots, K$, with $n = \sum_{k=1}^{K} n_k$ the total number of DMUs and $j_k = 1, \ldots, n_k$, is the technical efficiency of the DMU_{j_k}, of the group k, respect to the DMUs of its group k.

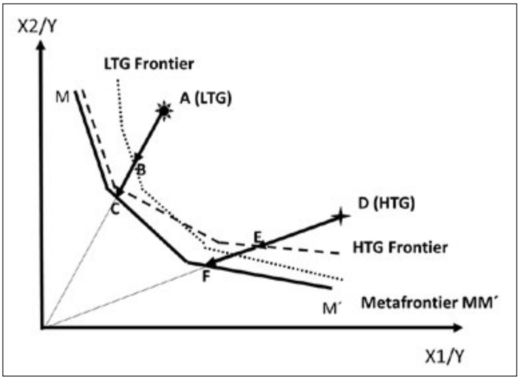
In addition, the metafrontier (MM') is estimated taking into account all the n DMUs, i.e., all the DMUs of both technological groups. The efficiency of the DMU_{j_k} regarding this metafrontier is denoted by TE_{j_k}, $j_k = 1, \ldots, n_k$, and $k = 1, \ldots, K$.

The meta-technology ratio (MTR_{j_k}) is the ratio between both efficiencies, i.e., $MTR_{j_k} = \dfrac{TE_{j_k}}{TE_{j_k}^{k}}$, when the DMU_{j_k} belongs to the technological group k. This ratio represents the ratio between the distances to both frontiers.

After compute the different efficiency indexes, their distributions were compared. To do that, the test of Simar-Zelenyuk (Simar and Zelenyuk, 2006) was performed with 1000 replications, as it is required to compare distributions of technical efficiency scores. In addition, the Two-sample Kolmogorov-Smirnov equality test for distribution functions, and the Kruskal-Wallis equality-of-populations rank test were applied.

Besides the efficiency estimation, additional analysis was conducted, in order to detect the management effect on the dairy-sheep production-system efficiency in Castilla-La Mancha. It is a well-known general result that, if the endogenous variable is bound, truncated regression

Figure 1 - Production Metafrontier.



and bootstrap techniques are suitable to its estimation (Simar and Wilson, 2007). Thus, truncated regression models were estimated, with 1000 bootstrap samples, to explain the calculated efficiency index *TE* with a set of *L* efficiency factors by the *F* function, i.e. $TE = F(\beta, f) + \varepsilon$, with $\varepsilon \in N(0, \sigma^2)$, and $0 < TE < 1$.

For this model estimation, the Simar and Wilson (2007) algorithm #1 was applied, using Stata software, and the package "simarwilson" developed by Badunenko and Tauchmann (Badunenko and Tauchmann, 2016).

A firm is inefficient because it obtains less output than its target, which is on its production frontier, using the same inputs and similar technology. If it used the inputs optimally, it would be efficient. Its inefficiency may be due to factors that are modifiable in the short term, and are mainly related to management.

The variables, which can influence the farm efficiency, were included as explanatory variables. These variables have been selected based on our own knowledge of the sector and those considered in previous works (Ozden and Dios-Palomares, 2016; Urdaneta *et al.*, 2013).

The following variables were selected:

- The variable TG (Technological Group), which indicates the farm technological group. It is equal to 0 for (LTG) and equal to 1 for (HTG). The group is included so that the two different groups are considered in the independent term. In principle, it is to be expected that the companies in the HTG group, in addition to being more productive, are also more efficient.

- The variable STTI. Its value lies between 0 and 1. The STTI index consists of the technologies listed in Table 4. All of them refer to actions that can be changed in the short term. Preliminary studies have established a positive relationship between efficiency and farm intensification through the implementation of technologies (Cabrera *et al.*, 2010; Álvarez *et al.*, 2008). These short-term technologies include the acquisition of equipment and the adoption of good farming practices. They also ensure proper management of inputs available on farms during the different seasons of the year, resulting in better reproductive performance and milk yields of ewes. Their application is expected to favour productivity and, thus, technical efficiency.
- The associative index, which takes the value 1 when the farmers are members of associations, and 0 otherwise. The percentage of associative farms was 37.7%. The farms that are members of associations should receive information and have advantages that could favour efficiency. Better planning is directly related to production success (Morantes *et al.*, 2014)
- The indexes of organisation (OI) and control (CI). Both indexes are valued between 0 and 1. These indices contain variables that cover organisational and control aspects, as expressed in section 2.1 of this paper. The implementation of these aspects may imply an improvement in efficiency (Morantes *et al.*, 2014).

The data were analysed with the following software: Banxia FRONTIER 3.0 (2003), SPSS (2013), STATA (2015), FEAR (Wilson, 2008) and R (R Development Core Team, 2010). In addition, we have developed a program based on the *np* routine of R, to apply the Simar-Zelenyuk test in this paper.

3. Results and discussion

3.1. *Evaluation of long and short term technological strategies*

Table 3 collects the management strategies taken into account in the long-term technological index (LTTI) and their percentage of use in the studied systems. These percentages show that the more implemented technologies are mechanical milking, and separate shepherding by production group. The other collected strategies are less implemented in the studied systems.

Many farmers do not follow genetic criteria for the breeding and replacement of flocks and herds. This lack could be negative for the farms productivity level. This issue was pointed out by researchers like Solano *et al.* (2000). There are only a few farms with technical feeding procedures. Equipment as feeding belts, silos, and haylofts usually lacks. Diverse research suggests incorporating automatic feeding due to its positive effect in cow milk production (Van Asseldonk *et al.*, 1998). In addition, it is also verified that the use of hay store strategies and silage have a positive relation with scale production in dairy sheep production systems (Gabbi *et al.*, 2013; Bernardes and do Rêgo, 2014).

The study indicates that a low proportion of the farms have implemented the use of troughs of cement and dungheaps. The implementation of these technologies is directly related to ammonium emissions in livestock production systems (Monteny and Erisman, 1998). Thus, these technologies could be indicators of the animal wellbeing, environmental conditions, and job performance of the workers and farmers.

Table 3 also shows the weights assigned by the experts to each strategy. The results indicate that the experts have similarly weighted management practices included in the LTTI. Shepherding and the use of genetic criteria for breeding and ram replacement were technologies better assessed and they received higher weights by the experts.

The results of the descriptive analysis of the Long Term Technological Index (LTTI) are collected in Table 5.

The LTTI has a low average value of 0.41 points with standard deviation s.d. = 0.24. However, the values vary between the minimum value 0 and the maximum value 0.90. This large range of variability illustrates a great heterogeneity of the technological development of the studied farms. Thus, it is convenient to detect homogeneous groups regarding technology before the estimation of the technical efficiency.

Table 5 - Description of long-term technological index (LTTI) and short-term technological index (STTI).

Variable	*Mean*	*Standard deviation*	*Minimum value*	*Maximum value*
Total sample				
Long-term technological index	0.41	0.24	0	0.90
Short-term technological index	0.59	0.16	0.23	0.89
HTG Group				
Long-term technological index	0.49	0.20	0	0.89
Short-term technological index	0.67	0.16	0.29	0.89
LTG Group				
Long-term technological index	0.38	0.24	0	0.90
Short-term technological index	0.57	0.16	0.23	0.89

Table 4 has the same structure that Table 3, but concerning the strategies of management in a short term included in the Short Term Technological Index (STTI). They are the management practices that could be easily changed. Third column shows that there are eight strategies applied in a proportion greater than 80%. However, it could be also checked that the less developed feeding strategy is the use of batches of animals, where batches are done taking into account the nutritional requirements at milking times. Despite the fact that they are easy to implement and do not require high investment, some breeding strategies, like male effect and flushing, are performed in a low proportion. A high proportion of farms does not apply mastitis vaccines, and does not provide vitamins and minerals for the lambs.

The values of the weights proposed by the experts are quite similar among the different management practices. They are collected in Table 4 and vary between 0.03 and 0.06.

The descriptive values of the STTI are shown in Table 5. The results indicate an average value around 0.60 (with s.d. = 0.16). Thus, the level of application of these practices is medium-high, although a large dispersion exists. This variability shows that a relation could be present between the medium-high level of application of these practices and the technical efficiency. Such relation deserves to be studied and analysed. In fact, it is interesting to know if the farms that apply these strategies are more efficient than the other farms.

3.2. *Technical efficiency and metafrontiers*

Before the analysis of the technical efficiency, the heterogeneity of the technology is studied. To do it, the multivariate methodology described in Section 2.3 is applied.

A factorial analysis was done to the partial productivity indicators and the LTTI. Two factors were obtained and they explain the 78.6% of the variance.

A cluster analysis of *K* means was performed. In accordance with the results obtained, the farms were divided into two groups.

The group 1 (with $n_1 = 42$ farms) with a high technological level (HTG); and the group 2 (with $n_2 = 115$ farms) with a low technological level (LTG). Table 6 shows the productivity values. Average and standard deviation are detailed in the two groups separately. Mean-difference tests were performed with the t-Student test. Significant differences ($p < 0.01$) were found between the two technological groups.

In Tables 3 and 4 we can see the percentages of use of the strategies that make up the LTTI and STTI indices, respectively, separated by groups.

Regarding the LTTI index, only the strategies of mechanical milking, and separate shepherding by production group have similar percentage of application in both groups. We found interesting differences in the rest of strategies between the two technological groups. The greater percentage of application of the strategy occurs in the high technology group HTG. This difference is especially relevant in the use of genetic values as criterion for

Table 6 - Productivity and long-term technological index (LTTI) by technological group.

Variable	*HTG* *n = 42*	*LTG* *n = 115*	*t- student*
	Mean (sd)	*Mean (sd)*	
Long-term technological index	0.49 (0.20)	0.38 (0.24)	2.75*
Milk (L)/Ewe	197.39 (50.23)	126.34 (42.95)	8.76*
Income from Milk Sales (€)/Ewe	241.15 (75.89)	153.99 (66.32)	7.01*
Total Sales Income (€)/Ewe	392.99 (107.67)	306.25 (112.99)	4.31*
Gross Margin (€)/Ewe	194.92 (96.89)	116.55 (109.39)	4.09*
Milk (L)/UAW	49519 (19344)	30969 (17190)	5.79*
Income from Milk Sales (€)/UAW	59715 (23674)	36945 (21749)	5.67*
Total Sales Income (€)/UAW	99568 (46025)	73889 (39653)	3.44*
Gross Margin (€)//UAW	50973 (35237)	30526 (30476)	3.57*
Milk (L)/ha	303.97 (157.70)	94.84 (52.52)	12.50*
Income from Milk Sales (€)/ha	369.22 (201.01)	111.20 (56.22)	12.55*
Gross Margin (€)/ha	299.08 (249.15)	83.28 (76.26)	8.32*

*HTG: high level technological group, LTG: low level technological group, sd: standard deviation, n = number of farms, L: litres, €: euros, ha: hectares, UAW: unit of agricultural work, *: P < 0.01.*

replacement and the use of feed belt. These results confirm the definition of the groups considering their technological level, and suggest the presence of a technological gap. This gap is also shown in Table 5. The mean of the LTTI index is 0.49 in the HTG group and 0.38 in the LTG group.

There are also important differences in the application of the strategies included in the STTI index when we compare between the two technology groups (Table 4). For almost all strategies, the percentage of application is higher in the HTG group than in the LTG group. The largest differences (around 35%) are found in assistant copulation, and artificial insemination. About the management strategies named manages lots of feed in the milking, having vacuum valve, and applying mastitis vaccine; their percentage of presence in the HTG group was around 12% higher than in the LTG group. These results indicate that firms with higher technology in the long term have also applied more technology in the short term. Furthermore, Table 5 shows that the average STTI index for HTG firms is 0.67, and for LTG firms it is 0.57.

In our research, two production frontiers are expected. Taking into account this structure of two technological groups, metafrontier methodology is applied for the efficiency analysis.

The analysis of the atypical data (outliers) by the method of Wilson (1993) identified 10 outliers in the HTG group and 9 outliers in the LTG group. These outliers were removed. As a result, the HTG group was reduced from 42 to 32 farms, and the LTG group from 115 to 106 farms.

Descriptive values of the variables considered in the Data Envelopment Analysis (DEA) are shown in Table 7.

These values are reported separately in the two technological groups. Differences are observed between the two technological groups. In average, the farms of the HTG group use greater values of the following inputs: ewes (*n*), unit of agricultural work (UAW), fixed capital (€), and working capital (€). These farms also produce, in average, greater levels of output. In addition, the farms with low technological levels (LTG group) present lower levels of output. However, they use more amount of land (ha). This fact indicates that the production system of the farms of this group is more extensive, considering the ewe/land ratio.

Table 8 shows the descriptive measures (mean and standard deviation) of the Meta-frontier es-

Table 7 - Mean, standard deviation, minimum and maximum of output and inputs for groups of farms of high and low technological levels.

	HTG				*LTG*			
	Mean	*sd*	*min*	*max*	*Mean*	*sd*	*min*	*max*
Output								
Milk (L)	174050	107811	31000	456000	81875	57729	6500	246000
Inputs								
Ewe (n)	843	541	267	2512	623	367	81	1751
UAW	3.66	2.15	1.33	9.67	2.65	1.22	1	6
Land (ha)	758	567	39	2200	939	670	100	3200
Fixed capital (€)	41677	29334	12191	142019	28357	18561	1622	83133
Working capital (€)	103765	67063	21113	257652	71825	47134	5477	230639

HTG: high level technological group, LTG: low level technological group, sd: standard deviation, min: minimum, max: maximum, L: litres, €: euros, ha: hectares, UAW: unit of agricultural work.

timation results, the statistics, and the statistical significance of the three tests applied. Second column indicates the size of each technological group. Columns 3 to 5 collect the corresponding technical efficiency (TE) indexes obtained by the classical CCR (Charnes *et al.*, 1978) and BCC (Banker *et al.*, 1984) DEA models and the scale efficiency SE, i.e., the efficiency indexes TE-CCR, TE-BCC and SE, respectively. The efficiencies of each technological group $TE_{j_k}^k$ are presented in the first set of rows in a separate way taking into account the corresponding frontier. The second set of rows show the efficiencies TE_{j_k} with respect to the metafrontier of each technological group. Note that the metafrontier is a unique frontier for all the firms. The third set of rows presents the metafrontier technological ratios MTR_{j_k}, also separated by technological groups. The statistics and the statistical significance of the three tests are reported in each set of rows in order to test the distribution differences between the two technological groups (HTG and LTG). These statistical tests are Kolmogorov-Smirnov, Kruskal-Wallis and Simar-Zelenyuk tests.

Regarding intra-group efficiencies, the results show that the farms of the high technological group (HTG) are, in average, significantly more efficient than the farms of the low technological group (LTG), and their distributions are significantly different. These differences are significant both, concerning the CCR-efficiency (CCR) and the pure technical efficiency (BCC). This result suggests that the farms with higher technological levels are closer each other regarding the management of the resources than the farms with lower technological levels. It is important to know that these values compute the distance of the farms to the frontier of their technological group. These scores are independent of the proximity of their group to the metafrontier. These results are consistent with those of Kompas and Che (2006). They concluded that the more efficient firms are those that also use forward technologies, like rotary or swing-ever dairy shed, and a greater amount of land under irrigation. Likewise, Ozden and Dios-Palomares (2016) applied metafrontier models and found similar results. The more productive firms were in turn more efficient.

In addition, the results also show a high level of scale efficiency (SE), equal for both technological groups. This indicates that, concerning their own technology, the majority of the firms of this economic sector work in their optimal size. Similar results were obtained regarding the dairy cattle to produce milk with scale efficiency values (SE) around 94.7% (Hansson, 2008).

The farms with lowest level of inputs (sheep (*n*), UAW = unit of agricultural work, fixed capital (€), and working capital (€)) have lowest values of CCR- and BCC-efficiencies. This result coincides with the previous results about dairy farms obtained by Kirner *et al.* (2007). These authors pointed out that the farms with low inputs present low levels of efficiency, due to their great reliance on the agrarian policy.

Table 8 - Indexes of technical efficiency, scale and meta-technological ratio.

	n	*CCR (sd)*	*BCC (sd)*	*SCALE (sd)*
Efficiency by group $TE_{j_k}^{k}$				
HTG	32	0.83 (0.13)	0.90 (0.12)	0.92 (0.09)
LTG	106	0.70 (0.21)	0.76 (0.19)	0.92 (0.09)
K-S		0.42*	0.37*	0.09
K-W (χ^2)		9.70*	12.47*	0.04
S-Z		4.86*	3.90*	4.9
Metafrontier TE_{j_k}				
HTG	32	0.83 (0.13)	0.89 (0.12)	0.93 (0.08)
LTG	106	0.52 (0.17)	0.59 (0.19)	0.88 (0.13)
K-S		0.79*	0.71*	0.17
K-W (χ^2)		54.40*	46.76*	2.42
S-Z		12.90*	12.87*	–0.83
Meta-technological ratio MTR_{j_k}				
HTG	32	1.00 (0.00)	0.99 (0.03)	1.00 (0.04)
LTG	106	0.74 (0.09)	0.77 (0.11)	0.96 (0.09)
K-S		0.99*	0.85*	0.63*
K-W (χ^2)		71.83*	56.46*	14.05*
S-Z		14.66*	21.44*	13.34*

*HTG: high level technological group, LTG: low level technological group, sd: standard deviation, n = number of farms, K-S: Kolmogorov-Smirnov test, K-W: Kolmogorov-Wallis test, S-Z: Simar-Zelenyuk test, *: P < 0.01.*

The estimates of the efficiency concerning the metafrontier show greater differences between the two technological groups than the differences pointed out by the separate and independent frontiers, as it was expected. However, in the scale efficiency, SE, it is observed only small differences between the means of both groups, and their distributions are not significantly different. These metafrontier estimations clearly show for the low technology group (LTG) lower values of the efficiency than the values computed with separate frontiers. In contrast, the estimated levels for the high technological group (HTG) in the metafrontier do not differ too much from the values estimated with separate frontiers. That is because the HTG-frontier is closer to the metafrontier than the LTG-frontier. In fact, in a great proportion, the metafrontier is defined by the HTG-frontier.

The meta-technology ratio takes the value 1 for the HTG. This means that the HTG-frontier of this high technology group practically coincides with the metafrontier. On the other hand, the values 0.74 and 0.77 for the LTG with the models CCR and BCC, respectively, show the distance between the LTG-frontier and the metafrontier.

Table 9 indicates the number of efficient and inefficient farms for the indexes TE-CCR, TE-BCC and SE, respectively. It is also shown the two approaches, the measures with respect to the separate frontiers and concerning the metafrontier. The results collected in this table also show that the majority of the efficient farms of the LTG are inefficient regarding the metafrontier. However, this estimated distance to the metafrontier is mainly due to the lack of technology, and not truly to a real lack of efficiency. Similar results are reported in dairy cattle in New Zealand, where the agrarian technology is more developed in the south of the island than in the north (Jiang and Sharp, 2015).

The results of our study indicate that the production frontier for the farms of the LTG is far from the metafrontier. Therefore, there is a technological gap in the sector. About this conclusion, different studies propose the implementation of agrarian policies to help with the reduction of this technological gap. These papers suggest that the available technology must be applied to the local conditions for extending the production frontier of the group (Gatti *et al.*, 2012; Alem *et al.*, 2017; Melo-Becerra and Orozco-Gallo, 2017). To this aim, it would be necessary to increase investment in research and development to implement the new technologies. Also, Jiang and Sharp (2015) dealt with this problem and propose to promote actions of training and formation for the farmers.

Regarding our research, Rivas *et al.* (2015) studied the canonical correlation of technological innovation and performance in the same sample in Castilla-La Mancha. They agree with Dhraief *et al.* (2019) in pointing out the main determinants of the technological gap in these farms. Improvement in technology requires a minimum threshold production structure to ensure profits for the firm. Large companies implement innovation more easily than small ones. Large companies have more sheep, more land and are less dependent on external resources. They also have greater availability of capital. The use of these technologies has an impact on structural costs, but also increases output. Therefore, their impact on unit cost is lower.

Therefore, it is important that companies grow in size. In addition, it is also necessary for small companies to understand the process of technology adoption. Change involves managing systems with more complexity, considering a complete view of the process.

Thus, in order to reduce the technology gap, it is essential for companies to receive information, training and coaching. But especially, these companies need financial support and funding. This could prevent the abandonment of young entrepreneurs who are more willing to innovate. To this end, they could benefit from the aid provided by the agricultural policy measures that affect Castilla-La Mancha. The second pillar of the Common Agricultural Policy (CAP) of the European Union contemplates these measures. It is the current Rural Development Policy (EU Regulation No. 1305/2013 of the European Parliament and of the Council of 17 December 2013 on support for rural development by the European Agricultural Fund for Rural Development (EAFRD)), (ref. Official Journal of the European Union, 2013). One of the six priorities of this policy is "transfer of knowledge and innovation". This priority is articulated in a series of measures that seek to promote innovation and the knowledge base in rural areas (Article 14) thereby improving the competitiveness of all types of agriculture and the viability of farms.

Specifically, the RDP (Rural Development Programme) of Castilla La Mancha 2014–2020 includes among its measures the "M01: Knowl-

Table 9 - Frequency of efficient and inefficient production units.

	n	*CCR* *n (%)*	*BCC* *n (%)*	*SCALE* *n (%)*
Efficiency by group				
HTG	32			
Efficient		6 (18.75)	16 (50.0)	6 (18.75)
Inefficient		26 (81.25)	16 (50.0)	26 (81.25)
LTG	106			
Efficient		13 (12.3)	26 (24.5)	25 (23.6)
Inefficient		93 (87.7)	80 (75.5)	81 (76.4)
Metafrontier				
HTG	32			
Efficient		6 (18.75)	15 (46.9)	6 (18.75)
Inefficient		26 (81.25)	17 (53.1)	26 (81.25)
LTG	106			
Efficient		1 (0.9)	7 (6.6)	14 (13.2)
Inefficient		105 (99.1)	99 (93.4)	92 (86.8)

HTG: high level technological group, LTG: low level technological group, n = number of farms.

edge transfer and information actions (art. 14)" (ref. Rural Development Programme European Union, 2015).

Figure 2 draws the Kernel estimation of the density function for the TE-CCR index. It illustrates the results previously indicated. The distribution of the efficiency of the HTG is right-slid with respect to the distribution of the efficiency of the LTG. There is a greater proportion of farms of the HTG group with high level of efficiency.

Figure 3 shows the Kernel estimation of the density function for the TE-BCC index. A considerable proportion of the farms of the LTG group are low of the efficiency level of 0.85. The farms of the HTG group have efficiency levels substantially higher, and a large proportion of these HTG farms have efficiency level greater than 0.6.

The Kernel estimation of the density function for the SE index is drawn in Figure 4. It is observed high values and with a similar distribution for the farms of the groups LTG and HTG.

3.3. *Determinants of technical efficiency*

Besides the estimation of the efficiency levels, it is necessary a research work looking for the crucial factors that influence the efficiency, in order to solve the problem and improve efficiency.

The estimated truncated regression models obtained following Simar-Wilson (2007) methodology for the TE-CCR, TE-BCC and SE indexes for all the farms are reported in Tables 10, 11 and 12.

The estimated values for the parameters of the variable TG (Technological Group) in the technical efficiency CCR (TE-CCR) efficiency model are significant and positive (Table 10). Then, the HTG group is, in mean, more efficient than the LTG group. This fact confirms the obtained results in the efficiency analyses by group.

This model also presents positive values for the STTI. Thus, the farms with greater values of this index are more efficient. The company organises the production process better throughout the livestock cycle if it has lambing facilities and carries out controlled mating, male effect, flushing and artificial insemination. These technologies make optimal use of feed resources and available labour, due to the reduction of the seasonal effect.

A key determinant of farm performance is feeding. The use of technologies such as unifeed is associated with higher dry matter intake, better regulation of rumen function, and higher milk production. It also reduces the labour required to feed the herd (Bargo *et al.*, 2002; Cabrera *et al.*, 2010). Likewise, organising the milking herd by batches based on their productive level is a practice that enables farmers to serve animals with different nutritional needs, and the strategic use of feed resources.

A successful genetic programme must include the discard of females and males from the herd for voluntary causes. The prevalence

Figure 2 - Kernel estimator of density function for technical efficiency-CCR for high (HTG) and low (LTG) technological level farm groups.

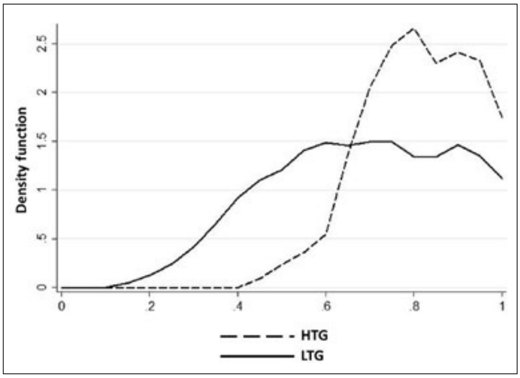


Figure 3 - Kernel estimator of density function for technical efficiency-BCC for high (HTG) and low (LTG) technological level farm groups.

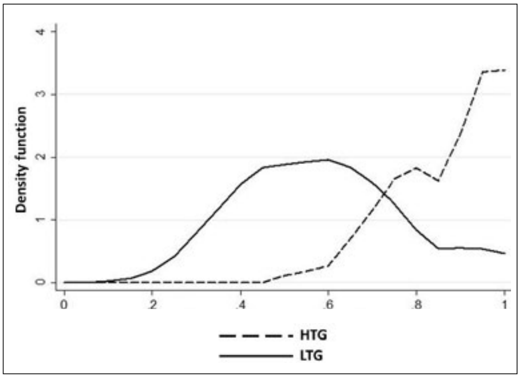
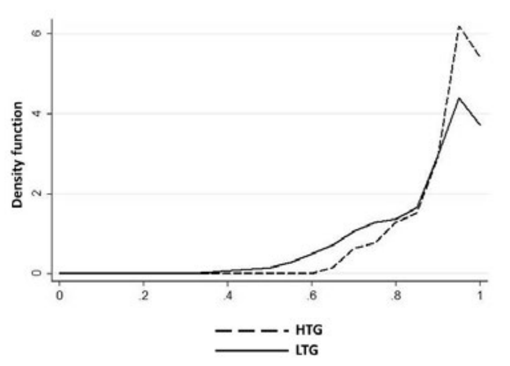


Figure 4 - Kernel estimator of density function for scale efficiency for high (HTG) and low (LTG) technological level farm groups.



of involuntary discards such as disease, injury, death, and infertility can limit the selection process, and negatively affect the productive performance of the farm.

Technologies related to herd health improve the efficiency levels of production systems. They comprise a correct milking routine, e.g. udder drying, cleanliness of facilities, etc. They ensure proper mammary gland health and milk quality, and are positively related to technical efficiency (Hansson *et al.*, 2011; Yilmaz *et al.*, 2020). In addition, vaccination protocols are necessary to avoid animal mortality and morbidity problems.

Concerning the organization and control indexes (OI and CI), Tables 10, 11 and 12 collect the results obtained. They are similar to the above commented results for the TG variable and STTI index. This means that the firms that pay more attention to these management functions are technically more efficient. In this respect, it is interesting to comment the conclusion of Bahta *et al.* (2015). These authors, in a study of beef cattle in Botswana, indicate that it is needed to promote services to the farmers in order to guarantee the implementation of breeding control methods in the herds, to improve efficiency of the farms.

Regarding the technical efficiency BCC (TE-BCC) (Table 11) the results are similar. There are observed significant differences of 6% between the two groups. TE-BCC efficiency values are used to compare farms of the same or similar size. Therefore, the technological level differences influence the productive level of the two frontiers, but not their TE-BCC efficiency. This last efficiency is higher in the farms where more attention is paid to managerial functions.

It is noticeable the negative and significant estimated coefficient for the variable which shows if the farmers are membership of association. In fact, the associated farms are about 15% less efficient than the others. This is a rare result because the associations are sources of important and useful information for the managerial functions. This result could be related to the fact that the associations promote investment for genetic improvement strategies of livestock, and such strategies could have a negative effect in production, if they are not implemented with a simul-

Table 10 - Models of the determinants of technical efficiency-CCR.

	Coefficient	*Standard error*	*Confidence interval 95%*		*P>z*
By group					
Constant	0.2914	0.0778	0.1462	0.4461	0.000
TG	0.1601	0.0497	0.0644	0.2693	0.001
OI	0.3188	0.0969	0.1359	0.5127	0.001
CI	0.1879	0.0592	0.0702	0.3033	0.002
STTI	0.3861	0.1484	0.0998	0.6758	0.009
Membership of association	-0.2168	0.0512	-0.3207	-0.1210	0.000
Sigma	0.1680	0.0144	0.1353	0.1918	0.000

Wald chi2 = 48.20
Prob > chi2 = 0.000
TG: Technological group, OI: Organisation index, CI: Control index, STTI: Short term technological index.

Table 11 - Models of the determinants of technical efficiency-BCC.

	Coefficient	*Standard error*	*Confidence interval 95%*		*P>z*
By group					
Constant	0.3978	0.0815	0.2386	0.5563	0.000
TG	0.1154	0.0619	0.0028	0.2529	0.062
OI	0.1981	0.0968	0.0106	0.3982	0.041
CI	0.1779	0.0599	0.0625	0.3013	0.003
STTI	0.3158	0.1570	0.0100	0.6297	0.044
Membership of association	-0.1494	0.0500	-0.2548	-0.0532	0.003
Sigma	0.1557	0.0145	0.1244	0.1800	0.000

Wald chi2 = 31.16
Prob > chi2 = 0.000
TG: Technological group, OI: Organisation index, CI: Control index, STTI: Short term technological index.

Table 12 - Models of the determinants of scale efficiency.

	Coefficient	*Standard error*	*Confidence interval 95%*		*P>z*
By group					
Constant	0.2517	0.1979	-0.1438	0.6048	0.203
TG	-0.1108	0.0807	-0.2708	0.0442	0.170
OI	1.1556	0.4288	0.4921	2.1257	0.007
CI	0.0853	0.1062	-0.1100	0.3114	0.422
STTI	0.7666	0.3501	0.1565	1.5532	0.029
Membership of association	-0.1694	0.1083	-0.4126	0.0240	0.118
Sigma	0.1640	0.0334	0.1037	0.2287	0.000

Wald chi2 = 8.72
Prob > chi2 = 0.1208
TG: Technological group, OI: Organisation index, CI: Control index, STTI: Short term technological index.

taneous improvement of the management. Similar results were found by Manevska-Tasevska and Hansson (2011) in their analyses of the key determinants factors in the efficiency of grape production farms. These authors showed that the membership of the farmers had a negative influence in the technical efficiency *TE*. They also conclude that these farmer associations do not fulfil their main objective to be a forum where the producers exchange ideas, share experiences, and work together to achieve better farm performance. In addition, Ozden and Dios-Palomares (2016) applied metafrontier models to olive oil firms in Turkey. They also considered the variable of membership of association, but, in this case, such variable did not present statistical significance. We also observe in our study that, actually, the associations do not influence to move the managers to start actions to achieve optimal results.

About these results, Siafakas *et al.* (2019) studied the dairy farms in Greece. They concluded that increasing available time spent, especially the farmer's own working hours, in effectively monitoring and managing livestock, and investing more in animal farming, would improve the farms' *TE*. Soliman and Djanibekov (2021) suggested that adopting on-farm management practices could be an option to improve dairy efficiency.

4. Conclusions

This paper investigates the efficiency level in dairy sheep systems in the Protected Designation of Origen (PDO) "Manchego Cheese" ("Denominación de Origen Protegida" (DOP) 'Queso Manchego') in Castilla-La Mancha, Spain, taking into account the heterogeneity related to the technological levels of the farms. Synthetic indexes are designed and computed in order to provide a proper and realistic assessment of the existing technologies.

The long-term technological index, wherein technologies that require considerable investment are included, shows that there is a great heterogeneity. Based on this index, and the partial productivities, two different groups were found. These two groups, with different and contrasting technological levels, are called High Technological Group (HTG) and Low Technological Group (LTG). The HTG has an average value of the LTTI of 0.49, while the average value of this index for the LTG is 0.38. Concerning the value of the Gross Margin by hectare, the LTG achieves, in average, about 72% lower than the HTG does. The former group includes farms with an area around 24% greater than the mean surface.

Efficiency is estimated with the Data Envelopment Analysis (DEA) methodology with metafrontier models considering these two technological groups. The obtained results show that the farms of the HTG are more productive, work with higher technological levels, and report, in average, a value of technical and pure efficiency about 18% greater than the farms of the other group.

If HTG technologies were applied to the farms of the LTG group, a production increase greater than 23% could be obtained. Concerning the scale, however, new technologies could offer only a reduction of the 4% in the average scale-inefficiency value. In addition, the results indicate the influence of the technological group. This fact also advises that the metafrontier approach applied is suitable to estimate efficiency. The analysis of the efficiency with metafrontier models guarantees that inefficiencies are not misleading with technological gap.

Short-term managerial strategies, which are evaluated with the synthetic index STTI (Short Term Technological Index), influence the efficiency levels of both technological groups. Similarly, farms that pay special attention to managerial functions achieve better efficiency results. However, farmers who are members of associations present lower levels of efficiency than others do. This shows that the associations are not working in an appropriate way, as it could be expected.

The efficiency level of the dairy sheep systems in Castilla-La Mancha could be improved, mainly in the farms with low technological level. Therefore, it could be very interesting to provide to these farms the investment and required means to implement the new technologies. Among them, it could be remarked the application of automatic feeding techniques like feed belt, the use of troughs of cement, dungheaps, silos, silage and hayloft. In addition, flushing and directed breeding are required practises which are not too much applied in the studied farms. One means of implementing these technologies is to increase the size. Finally, a special attention to the managerial functions, mainly organisation and planning is also advisable.

It is very important for entrepreneurs to inform themselves and to apply for the agricultural subsidies currently in force. However, these subsidies do not reach the companies easily. The associations should provide the farmers with the necessary means to obtain these subsidies. On the other hand, we urge the government to improve the agricultural policies that this economic sector needs.

These actions will increase the efficiency of these farms, and, consequently, their resilience and sustainability.

These conclusions can be applied to these Spanish farms and, in addition, to similar farms in the Mediterranean Basin.

Acknowledgements

The authors wish to thank the editors and the anonymous reviewers for their useful suggestions and comments. The authors are grateful to the Central University of Venezuela (CDCH-UCV); to the Spanish National Institute for Agriculture and Food Research and Technology

(INIA), in conjunction with regional authorities, Project: "Level of competitiveness of the dairy sheep production system, Manchego Cheese PDO" (RTA2011-00057-C02-02); and to the Spanish Government Research Project MTM 2017-84150-P, which is co-financed by the European Regional Development Fund (ERDF); for their financial support.

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