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Technical efficiency in the Spanish agrofood industry

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Abstract

This study estimates frontier production functions with cross-section data for the Spanish agrofood industry by using deterministic and stochastic parametric approaches. We compute the individual technical efficiency for each firm, compare the results and explain the relationship between technical efficiency and other relevant quantitative variables. The results indicate that the Spanish agrofood industry has a level of efficiency between 68% and 93%; which means that it is potentially capable of increasing production without increasing its consumption of inputs. This efficiency level is positively related to factor productivity and unitary labour costs. © 1997 Elsevier Science B.V.

Keywords: Spanish agrofood industry; Technical efficiency; Stochastic frontier

1. Introduction

In the last few years, a series of methods has been developed to determine the technical efficiency of production units. The analysis of technical efficiency aims at evidencing one of the factors that determine the competitiveness of a company or that of an economic sector. It is well known that competitiveness depends on a large set of both macroeconomic and microeconomic elements. It could be said that analysis of technical efficiency serves to focus on one of the mentioned factors from the microeconomic viewpoint. The implicit hypothesis in our approach is that if a company or productive branch is more efficient than any other, it is also likely to be more competitive.

In this work some of these methods are applied to the study of the technical efficiency of the Spanish agrofood industry (SAI). Considering its size, this industrial sector is fundamental to the Spanish economy, it is also of great strategic importance because of its close relationships with the agrarian sector. However, no specific investigations into its technical efficiency level have, as yet, been carried out.²

This type of analysis is intended to provide a global measurement of the productivity of each of the participants in a particular sector. As there are various ways of doing this, the following paper seeks to study the similarity or disparity of the levels of

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² Analyses were carried out of the technical efficiency of agrofood industry for two Spanish regions: Aragón (see Feijoo and Pérez y Pérez, 1994) and Navarra (see Goñi et al., 1995). In addition, Berges Lobera et al. (1986) analyzed the technical efficiency of a set of large industrial companies in Spain and Europe and obtained a technical efficiency index of the Spanish agrofood industry with respect to those of the rest of Europe.

Table 1

Data for agrofood industries in Spain and Europe, 1991

	Spanish agrofood industry (1)	Spanish industry (2)	European agrofood industry (3)	(1)/(2) (%)	(1)/(3) (%)
Number of firms	40,536	162,393	264,101	24.96	15.35
Number of employees	362.45	2,197.05	2,455.90	16.50	14.76
Production value ^a	6,109.79	31,481.01	55,805.30	19.41	10.95
Gross value added ^a	1,692.27	11,652.59	12,406.46	13.95	13.64
Number of employees/firm	8.94	13.53	9.30	66.09	96.13
Production value/firm ^b	150.72	193.86	211.30	77.76	71.33
GVA/employee ^c	4,668.99	5,303.73	5,051.70	88.03	92.42
GVA/worked hour ^c	2.68	3.10	—	86.45	—
Labour costs/employee ^c	3,056.39	3,792.99	—	80.58	—
Intermediate construction/GVA ^d	2.61	1.70	3.49	153.53	74.78
Labour costs/GVA ^e	42.92	49.61	—	86.51	—
GOS/production value ^e	15.81	18.65	—	84.77	—
GVA/production value ^e	27.70	37.01	22.23	74.83	124.61

^aThousand million pesetas.^bMillion pesetas.^cThousand pesetas.^dPesetas.^eIn percentage.

GVA: Gross Value Added. GOS: Gross Operating Surplus. Source: Instituto Nacional de Estadística, Eurostat and authors' own.

technical efficiency obtained through different methods.

In Section 2, the main characteristics of the Spanish agrofood industry are outlined using aggregate information. Section 3 contains a description of the methods used to estimate frontier production functions and calculate the technical efficiency level. Section 4 deals with the sources of information used in the estimation as well as with their limitations. Section 5 contains the results obtained and analyses the relationship of the technical efficiency level with other relevant quantitative variables. Section 6 summarizes the key results.

2. Characteristics of the Spanish agrofood industry

The Spanish agrofood industry has considerable relative importance, both within the national and European framework. At domestic level it occupies 16.5% of the workforce and accounts for 19.5% of the value of industrial production. Furthermore, it provides more than 10% of the added value of the European agrofood industry, surpassed only by the agrofood industries in Germany, France and the UK.

One of the structural characteristics of the SAI is its small size per unit. As Table 1 shows, whether measured by the number of workers per firm or by the production value per firm, it is smaller than both the national and European Community industrial average, in spite of the fact that in the last few years many of the firms from the smallest strata have disappeared.³

The apparent productivity of the labour factor, per employment unit as well as per hour worked, is lower than the industrial average. Such low productivity can be accounted for by the lower intensity of physical and human capital which is to be found in agrofood production. Lack of technological development in this industry prevents it from increasing productivity and efficiency by means of innovation in processes and above all in products. In this respect, it must be taken into account that the agrofood industry is weak in demand and less well endowed technologically than other industries.

³ According to Rodríguez-Zuñiga and Soria (1985), in 1981 the average size was 7.7 workers per firm and the average production value was 49.9 million pesetas.

The close dependence of intermediate consumption on added value leads us to the assumption that these inputs have more bearing on the agrofood industry than is the case in industry as a whole. This is evidence of a lower degree of technological development.

The overall business results in the agrofood industry are inferior to the average for industry in general, both in gross operating surplus and gross value added per peseta produced. Surprisingly, the added value per unit of output is higher in the SAI than in that of Europe.⁴

In short, the indicators used show that the Spanish and European agrofood industries are, relatively speaking, not very efficient considering the fact that they have some high technical coefficients. They have low unitary labour costs and show a high dependency on intermediate consumption. Nevertheless, in spite of being a weak demand, low technology industry, both its central role in the agrofood production complex and the dynamizing effect of its development on agricultural production must be considered.

3. Methodology

When speaking about efficiency, three different concepts may be referred to: (1) Technical efficiency refers to the achievement of the maximum potential output from a given quantity of inputs, taking into account physical production relationships. (2) Allocative efficiency refers to the allocation of resources taking into account the prices of factors, and implies that the marginal product of each input must be equal to its price. (3) Economic efficiency is a term applied to the concept of overall efficiency, which includes allocative and technical efficiency.

The simplest approximations to technical efficiency are partial productivity indexes which relate the final output of the company to the resources used to produce it (the productive factors mostly used are labour and capital), but changes in output/input ratios are affected by changes in the combination of

different inputs and by changes in productive efficiency. Variations in these partial productivity indexes cannot be interpreted as variations in the efficiency of a particular resource, but as changes in the use of all the resources per unit of output (Prior et al., 1993). This is the principal limitation of these indexes.

A more consistent approach, initiated by Farrell (1957), is based on the estimation of a frontier production function. This function represents the technical relationships of production and serves to estimate the maximum output that can be obtained from a given combination of inputs. Units that are technically efficient will be located at the frontier, while those which are not will be below the frontier, since they obtain less output than is technically possible. The technical efficiency level can be calculated as the relationship between the output obtained ($\mathcal{T}$) and what would be attained if the units were located at the frontier ($\mathcal{T}^*$), that is to say, $0 \leq \mathcal{T}/\mathcal{T}^* \leq 1$.

However, the frontier production function is unknown; which raises the problem of how it may be estimated. In the available literature on this particular subject there are several methods of estimating these frontiers. According to these methods, a distinction can be made between parametric production frontiers and non-parametric frontiers.

In the estimation of non-parametric frontiers, no previously defined form is imposed on the frontier production function (this is known as Data Envelopment Analysis, DEA).⁵ The estimation technique used is linear programming, therefore, assumptions are not made on the stochastic properties of the used data.

Parametric methods consider frontier production as a parametric function of the inputs and start from a particular function (Cobb–Douglas, CES, Translog, etc.). Within this set we can distinguish between deterministic and stochastic frontiers.⁶

⁵ See, among others, Prior (1990), Field (1990), Ley (1991), Domenech (1992).

⁶ Applications of deterministic models are found, among others in Russell and Young (1983), Murua and Albisu (1993). Stochastic models are applied in Taylor and Shonkwiler (1986), Dawson et al. (1991), Lopez and Robert (1992), Caves (1992).

⁴ This information must be cautiously interpreted, since it may have frictional content. In previous years, of which we have some information, the situation was just the opposite.

In the deterministic models it is assumed that the error term, random disturbance, covers technical inefficiency, and can be estimated by linear programming or by econometric techniques. In the stochastic ones it is assumed that the error term has two components: a white noise which covers random effects on production outside the control of the decision unit, and an asymmetrical component. This last component measures technical inefficiency by the distance remaining in order to reach optimum value and is assumed to be the result of behaviour factors which come under the control of the decision unit. The estimation technique used is econometrics.

In this work deterministic and stochastic parametric frontiers are estimated. It is assumed that the production technology can be represented through a Cobb–Douglas production function. Use of econometrics makes it possible to use statistical inference on the results. Therefore, we start from a function of the type $y_i = A \cdot \prod_{j=1}^k x_{ij}^{\beta_j} \cdot \exp(\varepsilon_i)$, $i = 1, \dots, N$, which, linearly, becomes $T_i = \alpha + \sum_{j=1}^k \beta_j X_{ij} + \varepsilon_i$, where $T_i = \ln(y_i)$, $X_{ij} = \ln(x_{ij})$, $\alpha = \ln A$, y_i = production value, x_{ij} = inputs considered.

(1) Deterministic frontier: from among the possible approaches⁷ to this sort of frontier, that of Greene (1980) has been selected. This author demonstrated that consistent estimates can be obtained from the frontier production function using corrected ordinary least squares (COLS).

The technique is as follows: if the ordinary least squares (OLS) technique is applied, we obtain the best linear, unbiased and consistent estimates of the slope parameters (β), but we obtain a non-consistent estimate of the constant term, α . To solve this problem, the residuals obtained by OLS are used. The constant term is amended by adding the maximum positive residual to it, and in this way a consistent estimate of α is obtained. Once this process is accomplished, all the residuals have the correct sign: they are non-positive and at least one is zero.

Once the parameters of the frontier production function have been estimated, the technical effi-

ciency level of each observation will be given by $\exp(\varepsilon_i) = y_i / A \cdot \prod_{j=1}^k x_{ij}^{\beta_j}$.

The main advantages of this method of estimating are easy computation and the possibility of measuring the efficiency of each of the observations. However, it has an important limitation, since it does not allow for random errors. This implies that all the residual is considered as inefficiency.

(2) Stochastic frontier: a frontier of this sort has its origin in the attempt to solve the above mentioned limitation of deterministic frontiers. Thus, Aigner et al. (1977) and Meeusen and Van Den Broeck (1977) developed models in which it was assumed that the random disturbance had two components, that is, it was assumed that $\varepsilon_i = v_i + u_i$.

The error component v_i represents the symmetrical disturbance that captures random errors, erroneous data, etc., and is assumed to be identically and independently distributed as a $N(0, \sigma_v^2)$. The error component u_i is the asymmetrical term that captures the technical inefficiency of the observations and is assumed to be distributed independently of v_i , and to satisfy that $u_i \leq 0$. Therefore, statistical distributions for u_i must be selected for distribution on only one side. Aigner, Lovell and Schmidt (ALS) analyze the cases of half-normal and exponential distributions. Meussen and Van Den Broeck study only the latter.⁸

The non-positive disturbance u_i reflects that the output of each firm must be located on or below its frontier, $\alpha + \sum_{j=1}^k \beta_j X_{ij} + v_i$. Any deviation is the result of factors within the firm's control, such as the technical and allocative inefficiency, the efforts of the entrepreneur, and those of the firm's employees, among others. The frontier can vary randomly from firm to firm, for this reason it is stochastic, with a disturbance $v_i \leq 0$, which is the result of factors outside the decision-making process, whether favourable or unfavourable for the firm, such as climate, luck and machine performance, as well as errors in observing and measuring data.

The estimation method proposed by ALS is maximum likelihood (MLE). Starting from the density function of the addition of a symmetrical normal

⁷ See among others, Aigner and Chu (1968), Timmer (1970, 1971), Richmond (1974), Greene (1980).

⁸ Later, other stochastic frontier models were developed, such as those proposed by Stevenson (1980) and Greene (1990) which assume, for the asymmetrical term, a normal truncated and gamma distribution, respectively.

variable and a half-normal variable, and supposing that the production function is linear, they elaborate the likelihood function that must be maximized.

The density function of $\varepsilon = v + u$ is:

$$f(\varepsilon) = \frac{2}{\sigma} f^* \left(\frac{\varepsilon}{\sigma} \right) \times [1 - F^*(\varepsilon \lambda \sigma^{-1})], \quad -\infty \leq \varepsilon \leq +\infty,$$

where $\sigma^2 = \sigma_u^2 + \sigma_v^2$, $\lambda = \sigma_u / \sigma_v$

and $f^*(.)$ and $F^*(.)$ are the density and distribution functions of a standard normal. The log likelihood function, if there are N observations, can be written as:

$$\begin{aligned} \ln L(y|\beta, \lambda, \sigma^2) \\ = N \ln \frac{\sqrt{2}}{\sqrt{\pi}} + N \ln \sigma^{-1} \\ + \sum_{i=1}^N \ln [1 - F^*(\varepsilon_i \lambda \sigma^{-1})] - \frac{1}{2\sigma^2} \sum_{i=1}^N \varepsilon_i^2 \end{aligned}$$

Once λ and σ are obtained, σ_u and σ_v can be calculated.

If the asymmetric error term is distributed as an exponential, the density function of ε is:

$$f(\varepsilon) = \frac{1}{\phi} \left[1 - F^* \left(\frac{\varepsilon}{\sigma_v} + \frac{\sigma_v}{\phi} \right) \right] \exp \left[\frac{\varepsilon}{\phi} + \frac{\sigma_v^2}{2\phi^2} \right]$$

The log likelihood function that is to be maximized is:

$$\begin{aligned} \ln L(y|\beta, \sigma_v, \phi) \\ = N \left[\ln \frac{1}{\phi} + \frac{1}{2} \left(\frac{\sigma_v}{\phi} \right)^2 \right] \\ + \sum_{i=1}^N \left[\ln F^* \left(\frac{-\varepsilon_i}{\sigma_v} - \frac{\sigma_v}{\phi} \right) + \frac{\varepsilon_i}{\phi} \right] \end{aligned}$$

An implication of this model is that the efficiency of each observation can be estimated by the ratio $y_i/A * \prod_{j=1}^k x_{ij}^{\beta_j} * e^{v_i}$ instead of by the ratio $y_i/A * \prod_{j=1}^k x_{ij}^{\beta_j}$. In any case v_i is not observable, therefore such a ratio can not be calculated.

However, given the assumptions of the distribution of v and u , Jondrow et al. (1982) calculated the

conditional mean of u_i given ε_i , the $E(u_i|\varepsilon_i)$. If u_i is distributed as a half-normal,

$$\begin{aligned} E(u_i|\varepsilon_i) &= \frac{\sigma \lambda}{1 + \lambda^2} \\ &\times \left[\left(\frac{f^*(\varepsilon_i \lambda / \sigma)}{1 - F^*(\varepsilon_i \lambda / \sigma)} \right) - (\varepsilon_i \lambda / \sigma) \right] \end{aligned}$$

If u_i is distributed as an exponential:

$$\begin{aligned} E(u_i|\varepsilon_i) &= \sigma_v \left[\left(\frac{f^*(\varepsilon_i / \sigma_v + \sigma_v / \sigma_u)}{1 - F^*(\varepsilon_i / \sigma_v + \sigma_v / \sigma_u)} \right) \right. \\ &\quad \left. - (\varepsilon_i / \sigma_v + \sigma_v / \sigma_u) \right] \end{aligned}$$

Once the $E(u_i|\varepsilon_i)$ is known, the efficiency of each observation can be estimated as the $\exp(-E(u_i|\varepsilon_i))$.

4. Data

The data to be used in the estimation of frontier production functions were supplied by the National Institute of Statistics (Instituto Nacional de Estadística, INE); and were taken from the corresponding Industrial Survey for 1991. Since the information source is the Industrial Survey, it should be pointed out that it does not include all agrofood industries, since part of the survey was conducted by the Ministry of Agriculture, Fisheries and Food (Ministerio de Agricultura, Pesca y Alimentación). The industries that are covered, according to the National Classification of Economic Activities (Clasificación Nacional de Actividades Económicas, CNAE) are the following:

CNAE	Included activities
411	Manufacture of vegetable and animal oils and fats
415	Processing and preserving of fruit and vegetables
416	Processing and preserving of fish and other sea foods fit for human consumption
417	Grain milling
418	Manufacture of spaghetti, macaroni, etc.

419	Bread and flour products
420	Sugar manufacturing and refining
421	Manufacture of cocoa, chocolate and sugar products
424	Distilling of ethyl alcohol from fermented materials: spirit distilling and compounding
427	Brewing and malting
428	Manufacture of soft drinks, including the bottling of natural spa waters

Moreover, given the statistical confidentiality of the data, the INE supplied only averages of three firms per group of the CNAE and per employment size category. The size categories are the following:

1. Less than 20 employees
2. From 20 to 49 employees
3. From 50 to 99 employees
4. From 100 to 499 employees
5. 500 and more employees

Therefore, the available information does not refer to individual firms. This represents one of the limitations of our work which must be taken into account when evaluating the results.⁹ Given the absence of alternative sources of information, each average is considered to be an individual observation. The frontier production functions and indices of technical efficiency obtained are assumed to be good approximations of those which would be obtained from individual data.

The variables included in the frontier production functions are as follows: the output of the firm is the value of production, VPRO; the inputs included are the number of employees, EMP (the mean of the employees at the end of each quarter) as a measure of the labour factor consumption; the consumption of raw materials, CRM; and, since relative information about the firm's capital is not requested in the Industrial Survey, a 'proxy' variable, ENE, representing energy consumption costs, is used.

The utilization of economic magnitudes for the estimation of production functions, which capture technical relationships of production, is another limi-

tation. The analysis can be biased, since we include the relative prices of inputs and outputs (the level of technical efficiency obtained incorporates part of the allocative inefficiency). Given the heterogeneity of inputs used and outputs obtained by agrofood industries, it is preferable to use the economic measure which permits us to accomplish the analysis in homogeneous magnitudes for all the industries considered. In addition, due to the difficulty of obtaining information on physical magnitudes, monetary magnitudes are necessarily used.

Initially there were 969 observations, from which 70 extreme observations, outliers, were eliminated. The reason for this (see Fz. de Troconiz, 1987, p. 169) is that they distort the regression equation since their incoherent values influence the estimation of the coefficients, giving them different values from those which would have been obtained from correct observations. The extreme observations are characterized by the great magnitude of the residuals they generate. The method used in our case to detect them is a studentized residual with an absolute value higher than two. Then, the number of available observations for the study is 899.

A summary of descriptive statistics (means and standard deviations) for the variables used in the analysis is shown in Appendix A.

5. Results

The frontier production function is estimated by assuming a conventional Cobb Douglas production technology:

$$\ln y_i = \alpha + \beta_1 \ln EMP_i + \beta_2 \ln ENE_i + \beta_3 \ln CMP_i + \varepsilon_i$$

Firstly, the average production function was estimated by the ordinary least squares (OLS) technique, which is used to obtain the deterministic frontier production function, adding the maximum positive residual to the constant. However, for this estimation of the average production function by OLS, the problem of heteroscedasticity exists (the Breuch–Pagan test has a value of 19.85). As a consequence, White's procedure was applied.¹⁰ Regarding multi-

⁹ The limitation emerges because the result of the aggregation of several Cobb Douglas production functions is not in itself a Cobb Douglas production function.

¹⁰ See Greene (1993, p. 391).

Table 2
Frontier production functions estimated^a

	Deterministic ^b	Stochastic (half-normal)	Stochastic (exponential)
Constant	3.207 ** (52.62)	2.923 ** (46.46)	2.888 ** (51.16)
lnEMP	0.275 ** (25.96)	0.2778 ** (26.85)	0.278 ** (26.36)
lnENE	0.130 ** (15.13)	0.130 ** (14.68)	0.130 ** (14.59)
lnCRM	0.644 ** (88.45)	0.642 ** (87.11)	0.642 ** (86.97)
$\hat{\lambda} = \sigma_u / \sigma_v$	—	0.864 ** (3.08)	—
$\hat{\sigma} = \sqrt{\hat{\sigma}_u^2 + \hat{\sigma}_v^2}$	—	0.304 ** (13.25)	—
$\hat{\sigma}_v$	—	—	0.159 ** (23.47)
$\hat{\phi}$	—	—	14.19 ** (4.76)
$\hat{\sigma}_u^2$	—	0.0179	0.0049
$\hat{\sigma}_v^2$	—	0.0239	0.0254
Log of the likelihood function	293.98	294.91	295.71
Average technical efficiency	0.677	0.899	0.932
$\bar{R}^2$	0.992	—	—

^aThe values in brackets are the *t*-ratios.

^bThe bias of the constant is amended and the values of the *t*-ratios are obtained by estimating the function with White's method.

* Statistically significant at 5%.

** Statistically significant at 1%.

collinearity, although it exists, as in all estimations of this type, it does not become serious.¹¹

The sum of the coefficients of three inputs considered equals 1.05, with an *F* statistic of 0.004. Therefore, it is accepted that slightly increasing returns exist in the Spanish agrofood industries.

As far as the estimation of the stochastic frontiers by MLE is concerned, the initial values for the maximization process were the estimates obtained by the method of moments proposed by Olson et al. (1980).¹²

The results obtained from the estimations of the frontier production function appear in Table 2. All the estimated coefficients are statistically significant at the 1% level, and the production frontiers estimated by the three methods do not present important differences, except in the constant term. However,

the technical efficiency levels do vary among the three methods used.

The average technical efficiency varies from 0.68 for the deterministic frontier to 0.93 for the stochastic frontier with the asymmetrical term following an exponential distribution. However, a difference exists between the deterministic frontier and the stochastic ones, because, in the first, all the residual is considered as inefficiency, while, in the other two, some of it is assumed to be random errors outside the firm's control. However, as Fig. 1 shows, the

Fig. 1. Individual efficiency levels ordered according to the half-normal frontier. DETEFF = technical efficiency calculated according to the deterministic frontier. HNOEFF = technical efficiency calculated according to the stochastic frontier, given an asymmetrical disturbance with a half-normal distribution. EXPEFF = technical efficiency calculated according to the stochastic frontier, given an asymmetrical disturbance with an exponential distribution.

¹¹ The rule followed to determine the gravity of multicollinearity was to compare the correlation coefficients between the variables included in the equation and the coefficient of determination (see Judge et al., 1988, p. 868). If the correlation coefficients are lower than the coefficient of determination, then multicollinearity is not considered serious.

¹² The statistic package used in the estimation by OLS as well as in the estimation by MLE was SHAZAM (Econometrics Computer Program, Version 7.0).

Table 3

Pearson and Spearman correlation coefficients^a

	DETEFF-HNOEFF	DETEFF-EXPEFF	HNOEFF-EXPEFF
Pearson correlation coefficient between efficiency levels	0.94	0.84	0.98
Spearman correlation coefficient between rankings produced	0.99	0.99	1.00

^aAll are statistically significant at 1%.

rankings of the observations according to the three methods considered coincide, since they follow parallel patterns.

To see if a relationship exists between the efficiency levels, Pearson correlation coefficients were calculated with the result that all are superior to 0.84 and statistically significant at the 1% level. Spearman correlation coefficients of the firms' rankings were also calculated for the three efficiency levels covered, and the same result was obtained. All are shown in Table 3.

Fig. 2 (and Appendix B) show the efficiency levels calculated for each of the activities covered by the study. The most efficient agrofood activities, according to the three methods studied, are those numbered 427, 418 and 428. The least efficient are those numbered 415 and 416. The inefficiency of the latter can be linked to a seasonal production pattern which implies a lower utilisation of the productive capacity. To determine whether these differences in efficiency levels among activities are statistically significant, an analysis of the variance was carried out. It turns out to be positive and statistically significant at the 1% level whichever efficiency level is calculated.

Finally, there is an evaluation of possible relationships between the efficiency and variables related to the firms. For this purpose, an analysis of the variance was used to determine whether there are significant differences in the means of the variables cov-

ered between the most efficient and the least efficient firms.

Thus, it is necessary to determine which firms are considered more and less efficient, a categorical variable depending on the analysis. The criterion adopted, for each efficiency level calculated, is that a firm is considered efficient if its technical efficiency is greater than or equal to the mean, and inefficient in any other case.¹³

With the available data, the variables taken into account are the following: individual factor productivities (PRODEMP, PRODENE, PRODCRM) as the relationship between the gross value added and the use of the labour, capital and raw material factors; the entrepreneurial size determined by the number of employees (EMP) or by the production value (VPRO); unitary labour costs (ULABC); and measures of economic performance assessed by the gross value added obtained per peseta produced (UGVA) and the gross operating surplus per peseta produced (UGOS).

Since the results obtained from the analysis of the variance are similar for three methods, Table 4 presents only those for the classification of the firms as more or less efficient according to the efficiency level obtained with the stochastic frontier when the asymmetrical term follows a half-normal distribution.

The first conclusion is that the most efficient firms obtain higher productivities out of the production factors, since the differences are statistically significant. This is an expected result, since, as already indicated, the efficiency level is an index intended to cover the individual productivities of the production factors collectively.

Fig. 2. Average efficiency per CNAE calculated from the three resulting frontiers.

¹³ It should be pointed out that this average varies at each efficiency level, and a firm can, therefore, be classified as efficient at one level and inefficient at another.

Table 4
Analysis of the variance with half-normal efficiency

	PRODEMP	PRODENE	PRODCRM	EMP	VPRO	ULABC	UGVA	GOS
Difference of means ^a	1,358.33	7.59	0.502	7.26	455,829.84	420.18	0.0917	0.0915
Statistic <i>F</i>	118.92 **	67.09 **	112.53 **	1.65	16.14 **	65.35 **	61.69 **	73.48 **

^a Value in the most efficient minus value in the less efficient.

** Statistically significant at 1%.

As far as the company size is considered, the results are disparate; since, if measured by the number of workers, the differences are not statistically significant, while, if measured by production value, the differences are significant at the 1% level, the largest firms being the more efficient. This disparity highlights the problem of measuring the size of the firms according to number of employees, since this figure is an average of four taken at different times during the year and, therefore, may not indicate exactly the amount of labour used. However, the correlation coefficient between the two measurements is superior to 0.80 and statistically significant at the 1% level.

The most efficient firms have higher unitary labour costs, indicating that the most efficient reward their workforce with higher returns in order to secure greater efficiency inputs. This result agrees with that obtained in other studies on efficiency.¹⁴ The positive relationship between efficiency and unitary labour costs can also be explained by the higher level human and technological capital available to the most efficient firms.

The relationship between efficiency and the firm's economic performance is also positive, since the most efficient obtain, on average, significantly higher GVA and GOS per peseta produced.

6. Conclusions

In view of the results, the first conclusion is that the frontier production functions obtained through the methods used involve a neutral transformation of the average production functions. However, the frontiers estimated produce different measures of techni-

cal efficiency, the most notable being differences between the deterministic frontier and the stochastic ones. However, the firms' ranking according to their technical efficiency level is independent of the frontier considered. To interpret the results, it must be taken into account that the absolute value of the efficiency level depends on the method used.

The level of average technical efficiency varies from 68% in the deterministic frontier to 90% in the stochastic ones. Clearly, the first overvalues inefficiency by considering all the residual as inefficiency. The problem with the stochastic frontiers is that a probability distribution must be chosen for the term that measures inefficiency. At any rate, the Spanish agrofood industry can increase its production without increasing the consumption of inputs, if these are used in a more efficient way.

As to the different activity branches considered, statistically significant differences between efficiency levels exist, with the mineral water industries (CNAE 428), the brewers (CNAE 427) and those manufacturing spaghetti, macaroni, etc., (CNAE 418) being the most efficient. The lesser efficiency in the vegetable and fish preservation industries seems to be related to seasonal production. In any case, it is possible that some of these differences in the efficiency level may be due to different production technologies employed in each activity. This could justify the estimation of a production frontier for each branch individually.

The relationship between technical efficiency and size is significant when the size is measured by production value. However, the result loses significance when the variable used is the number of workers. Technical efficiency in agrofood firms is related in a meaningful and positive way to factor productivities, economic performance and unitary labour costs.

¹⁴ See for example, Harris (1993).

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Appendix A. Descriptive statistics for the variables used in the estimation of frontier production functions

CNAE	Number observed	Production value (thousand pesetas)		Number of employees		Energy (thousand pesetas)		Raw materials (thousand pesetas)	
		Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
411	21	4,175,032	5,887,405	61.67	78.13	69,918	95,911	3,616,901	5,173,812
415	120	604,214	859,620	62.59	87.53	13,431	18,327	358,041	481,995
416	91	472,599	627,500	44.89	53.78	7,306	11,586	300,946	395,656
417	70	462,514	663,262	15.54	14.05	12,243	16,577	360,820	539,448
418	80	1,000,821	1,891,358	59.57	107.34	30,536	68,893	514,353	935,147
419	337	187,178	632,780	24.57	62.17	6,592	17,756	72,660	241,479
420	10	3,266,674	2,324,780	143.80	78.27	175,826	120,832	1,715,349	1,274,882
421	78	458,148	944,114	36.79	61.22	7,770	13,794	234,196	470,549
424	52	256,024	821,736	11.07	29.64	7,849	15,907	172,855	457,527
427	7	6,623,802	7,481,116	372.85	393.74	236,911	286,525	1,903,081	1,925,806
428	33	1,400,128	2,229,698	81.57	98.22	21,655	24,482	606,125	1,015,868
Total	899	615,122	1,703,509	41.39	84.11	16,031	48,701	350,312	1,094,784

Appendix B. Average technical efficiency in the food industries covered

CNAE	Number observed	Deterministic frontier		Stochastic frontier (half-normal)		Stochastic frontier (exponential)	
		Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
411	21	0.701	0.10	0.908	0.03	0.939	0.02
415	120	0.613	0.10	0.880	0.04	0.916	0.04
416	91	0.647	0.09	0.893	0.03	0.928	0.03
417	70	0.652	0.09	0.895	0.03	0.929	0.03
418	80	0.712	0.10	0.911	0.02	0.942	0.01
419	337	0.682	0.11	0.901	0.03	0.933	0.02
420	10	0.677	0.07	0.905	0.01	0.938	0.01
421	78	0.679	0.10	0.901	0.03	0.934	0.02
424	52	0.716	0.15	0.904	0.04	0.933	0.03
427	7	0.855	0.14	0.934	0.02	0.955	0.01
428	33	0.790	0.11	0.926	0.02	0.951	0.01
Total	899	0.677	0.11	0.899	0.03	0.932	0.03

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