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Food Industry Competitiveness across Europe:
An efficiency analysis

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Abstract. This paper calculates the food industry technical efficiency of a sample of 25 European countries over the period 2000-2003 as an indicator of competitiveness. Efficiency scores of the food industry across Europe are computed using a multi-input distance function. The analysis employs both parametric and non-parametric estimation of the distance function in order to provide a crosscheck on the efficiency scores. Also, convergence of the countries efficiency scores over the period is analyzed using sigma convergence. Our results indicate a strong degree of correlation between the results obtained by the alternative estimation methods. Overall, the EU-15 countries have usually higher efficiency scores than the incoming EU countries. Convergence of the efficiency scores suggests that the differences in efficiency performance of the countries have reduced over the studied period.

Keywords: Food-industry, efficiency, Distance Function, DEA, SFA, convergence Europe

La competitividad de la industria agroalimentaria en Europa: un análisis de eficiencia

Resumen: En este artículo se calcula la eficiencia técnica de la industria agroalimentaria de 25 países europeos para el periodo 2000-2003, como un indicador de competitividad. Para ello se utiliza una función de distancia multi-input, estimada tanto mediante métodos paramétricos como no paramétricos, lo que permite validar la consistencia de los índices obtenidos. También se analiza la convergencia en eficiencia de las industrias agroalimentarias de los países durante este periodo utilizando la sigma convergencia. Los resultados indican una fuerte correlación entre los índices de eficiencia obtenidos por ambos métodos de estimación. La eficiencia de los países de la UE 15 es mayor que la de los países del Este recientemente incorporados. La convergencia de los índices de eficiencia durante el periodo analizado sugiere que las diferencias entre los países se han ido reduciendo con el paso del tiempo.

Palabras clave: industria alimentaria, eficiencia, función de distancia, DEA, SFA, convergencia, Europa

Food Industry Competitiveness across Europe: An efficiency analysis

1. Introduction

Agricultural markets in Europe are facing new challenges due to the EU's Common Agricultural Policy (CAP) new orientation towards freer policies. Reduced market intervention for agricultural commodities has repercussions on the whole EU agro-food system, which will provide new opportunities or challenges for the European food products. The step-wise reduction of CAP measures intervention is leading to a convergence process on countries agricultural productivity levels. This trend is widely expected to continue, not least induced by upcoming World Trade Organization (WTO) commitments. The liberalization for agricultural commodities might have effects on food industries efficiencies across Europe. International trade is increasing more on food products than on agricultural commodities as market demand more transformed products. Those countries with more efficient food industries will be better positioned to gain markets. Transforming food products on countries where agricultural commodities are produced might not have clear advantages if their industrial system do not have a good performance.

The importance of the food industry, including all processing of food and beverages, to the EU national economies is illustrated by the fact that it is the first industry in terms of value added for countries such as Denmark, Spain, France, The Netherlands, Poland, Portugal and the UK, and the second in Belgium, Ireland, and Italy. The food industry is among the largest industrial activities within the EU-25, accounting for 185 billion of euros of added value and employing about 4.5 million persons in 2004. These figures equate to a 10.5% share of industrial value added and a 12.3% share of the total number of persons employed in the EU-25's industrial economy (Eurostat, 2005). Germany, France, Italy, the UK and Spain are the largest EU food and drink producers. They account to more than 70% of total EU turnover. France comes first with 136 billion euros of production in 2003.

There are many studies that deal with the effects of the CAP on the efficiency of agricultural production across Europe. However, there is a need to analyze the efficiency of the European food industry to discover economic opportunities and to encourage policies to adjust to the new environment. If EU countries are not sufficiently prepared to cope with the changing policy environment, the efficiency, competitiveness and sustainability of the European food system could be seriously affected. Since primary production and considerable parts of processing are located in rural areas, severe consequences for the prosperity of these areas can additionally be expected. Moreover, the increasing cross-border competition accompanying the convergence process raises the question as to the future structure of European food industry. The changing performances of the European food industry in terms of competitiveness will determine their role in the respective country economies.

In the economic literature there is no clear definition of competitiveness; it could be defined as the ability of a group to operate efficiently and productively in relation to similar groups (IDABC, 2005). Productivity can be defined as the ratio of output to input. In measuring productivity many studies have used partial measures such as the ratio of an output to a particular input (Deolalikar, 1981; Sen, 1962). However, several authors have argued that the use of partial measures of productivity is not correct since all inputs are not taken into account (Binswanger et al., 1995; Lund and Hill, 1979; Townsend et al., 1998; Van Zyl, 1996). Other studies use more complete measures such as total factor productivity (TFP), which is the change in total output relative to the change in the usage of all inputs (Coelli et al., 1998). The concept of efficiency means achieving maximum output from a given level of resources, adding to the concept of productivity an element of comparison to some known potential. Overall food industry productivity growth might be achieved by reducing inefficiency. If the sector is inefficient means that is using more resources and factor inputs than required by a particular technology, thus tying resources to low-productivity activities and reducing the overall allocative efficiency of an economy (Schreyer and Pilat, 2001). Then, in this paper, EU food industry competitiveness is measured by efficiency, therefore, the relevant issue becomes whether countries demonstrate greater overall efficiency (Gilligan, 1998) meaning, they are more competitive producing food products.

Thus, the aim of the paper is to asses the relative efficiency of the food industry across Europe to figure out whether the EU food industry, characterized by his small and medium size, is competitive in the new market environment, freer and more demand oriented. In this study, food industry performance for the EU-15 countries over the period 2000-2003 is analyzed relative to each other, by using multi input distance function to calculate the efficiency scores for several transformation processes. For this analysis the Eurostat data set is used to calculate efficiency of the food industry (NACE group 15, "manufacture of food products and beverages"), analyzing the efficiency of each sub-sector at the 3-digit desegregation level (groups 15.1 to 15.9). Different methodological techniques are used in order to compare their results and consistency. The analysis is complemented by introducing those countries from the EU enlargement that have data for the same period 2000-2003, in order to compare convergence of the countries efficiency scores. Convergence of the countries efficiency scores over the four year period is evaluated using sigma convergence. Sigma convergence provides information on whether or not country efficiency scores are converging over time, therefore reducing differences across countries.

The paper is structured as follows. Section 2 explains the approach used to measure efficiency and section 3 describes the data and the empirical application. Section 4 presents main results on cross-methodology comparisons, EU food industry efficiency levels and efficiency convergence estimates. Finally, some concluding remarks are presented.

2. Material and Methods

2.1. Measurement of efficiency

The concept of technical efficiency relates to the question of whether the best available technology is used in a production process. Distance functions provide an appropriate representation of the production technology (Kumbhakar and Lovell, 2000). Distance functions can be input or output oriented. An input orientation assumes that producers are capable of allocating resources when outputs are exogenous, while an output orientation focuses on the output mix while inputs are exogenous (Cuesta and Zofio, 2003). Assuming that the process uses a vector of *n* inputs, $x = (x_1,...,x_N) \in R_+^N$, to produce *m* outputs, $y = (y_1,...,y_M) \in R_+^M$, the input-oriented distance function is defined on the input set *L(y)* as follows (Shephard, 1970):

$$D_I(x, y) = \max\left\{\lambda : (x/\lambda) \in L(y)\right\}, \qquad (1)$$

where the input set *L(y)* represents the set of all input vectors *x* that are feasible for each output vector *y*, so that $L(y) = \left\{x \in R_+^N : x \text{ can produce } y\right\}$.

The distance function will take a value greater than or equal to 1 if the input vector *x* is an element of *L(y)*, and will take the value 1 if *x* is located on the inner boundary of *L(y)*. The distance function is closely related to Farrell's (1957) technical efficiency measure. Distance functions are used to define input oriented measure of technical efficiency as:

$$TE_I(y,x) = \min\{\theta : D_I(y,\theta x) \geq 1\} = [D_I(y,x)]^{-1}, \qquad (2)$$

The concept of a distance function was first introduced by Shephard (1953). The Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) are different methodologies used for distance function estimation and efficiency measurement. Linear programming techniques such as DEA, are commonly used to estimate distance functions (Cloutier and Rowley, 1993; Fandel, 1998; Fried and et al., 2002). More recently, some efficiency studies have estimated parametric distance functions using econometric techniques (Brummer et al., 2002; Coelli and Perelman, 1999; Fare et al., 1989, 2002; Murty and Kumar, 2002).

Comparison of studies using parametric as opposed to non-parametric estimation of distance functions indicates that there is no clear advantage of one method over the other and that the performance of the indicator depends on factors such as the number of units observed or noise in the data (Mortimer, 2002; Resti, 2000). DEA uses linear programming techniques to fit a boundary function to the observations. Deviations from the best practice frontier are due to technical inefficiencies and are assumed to be within the control of the firm. One important advantage of DEA is that it does not require specifying an explicit functional form for technology (Bauer, 1990). SFA is more restrictive in this respect but has the advantage of allowing for statistical noise (Jacobs, 2001). The deviation from the best practice frontier in SFA is a residual composed of a one-side inefficiency term indicating managerial incompetence and a symmetric random error term reflecting omitted variables and measurement errors.

2.1.1. Stochastic Frontier Analysis

The stochastic input distance function can be defined as (Hattori, 2002):

$$1 = D_I(x, y)\exp(-u + v) \tag{3}$$

where the error term is composed of *v*, which is a symmetric random disturbance term accounting for noise, and *u*, which is an asymmetric error term that accounts for production inefficiency. After estimation of equation (3), the predictor of the technical efficiency is obtained as the expectation of the term *u* conditional on the composed error *v-u*:

$$TE_I(x, y) = E\left[\exp(u)\middle| -u + v\right] \tag{4}$$

To estimate a stochastic distance function it is necessary to impose a functional form on the distance function. For this analysis we use a Cobb-Douglas function, an approximation to the true input distance measure is specified as (Coelli, et al., 2003):

$$\ln D_I(x, y) = \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_m + \sum_{n=1}^{N} \beta_n \ln x_n \tag{5}$$

where *x* and *y* are *N*x1 and *M*x1 vectors of inputs and outputs respectively.

To obtain an estimable function for the input-distance function, Coelli and Perelman (1999) make use of the homogeneity property. Imposing the homogeneity restriction on (7) by normalizing all inputs by an arbitrary input x_N yields:

$$\ln\left(\frac{1}{x_N}\right) = \ln\left(\frac{D_I(x, y)}{x_N}\right) + (-u + v) = \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_m + \sum_{n=1}^{N-1} \beta_n \ln\left(\frac{x_n}{x_N}\right) + (-u + v) \tag{6}$$

Maximum likelihood estimation of equation (6) will produce consistent parameter and efficiency estimates based on the stochastic input distance functions. The input distance functions are estimated using FRONTIER 4.1 software (Coelli, 1994).

2.1.2. Data Envelopment Analysis

DEA methodology uses linear programming techniques to measure efficiency as the distance of each unit from a non-parametric production frontier. For each inefficient unit, a measure of inefficiency is calculated by comparing its behavior with a reference unit located on the technological frontier (Reig-Martinez and Picazo-Tadeo, 2004).

Consider a sample of *s* countries, producing *m* outputs $y = (y_1, ..., y_M)$ with n inputs $x = (x_1, ..., x_N)$. Based on Farrell's ideas, Charnes et al. (1978) proposed a linear programming model to measure technical efficiency in the case of multiple outputs and multiple inputs, given by:

$$
\begin{aligned}
& \min_{\{\lambda, \theta_k\}} \theta_k \\
& s.t \quad \sum_{j=1}^{S} y_{rj}\lambda_j - y_{rk} \geq 0, \\
& \quad x_{ik}\theta_k - \sum_{j=1}^{S} x_{ij}\lambda_j \geq 0, \\
& \quad \lambda_j \geq 0,
\end{aligned}
\tag{7}
$$

where θ_k is the input-oriented Farrell's measure of total efficiency (E_k^T) of the k^{th} ($k \in S$) country and satisfies $0 \leq \theta_k \leq 1$. When θ_k = 1, the country is operating on the frontier. If θ_k < 1 the country does not operate on the frontier and is inefficient. The values of λ_j are weights attached to country *j* (*j=1,…,s*); y_{rj} is the *r*th output produced (*r=1, …, n*); and x_{ij} is the *i*th input used by that country (*i=1,…,m*). The constraints in (7) indicate that the weighted combination of other countries must produce at least as much of each output as does the k^{th} country (first constraint) without using more of any input than does country k (second constraint). The problem has to be solved S times, once for each country under evaluation.

Solution to problem (7) implies constant returns to scale (CRS). Thus, all countries are assumed to operate at an optimal scale. Banker et al. (1984) modified the above model to allow for variable returns to scale (VRS) by adding the constraint $\sum_{j=1}^{s} \lambda_j = 1$ to problem (7).

2.2. Data and empirical application

For a given input-output vector, the efficiency frontier is expressed in terms of minimizing the input requirement per unit of output in the context of Farrell's efficiency. For this analysis Eurostat database is used to provide data on inputs and output. One output variable and three input variables are used to estimate the parametric and stochastic input distance function. The inputs used are: (1) capital investments (in constant euros), (2) labor (number of workers), and (3) cost of other inputs (in constant euros); y is the output produced by each sub-industry (3-digit level) measured in euros. The distance function will take a value greater than or equal to 1 if the input vector x is an element of $L(y)$, and will take the value 1 if x is located on the inner boundary of $L(y)$. The data covers the period from 2000 to 2003 for 25 European countries and 9 food industries. The information for some of the countries was incomplete; therefore the number of countries analyzed varies for the different industries. The food industries considered are (total number of countries in brackets):

(1) da151: Production, processing, preserving of meat and meat products (24 countries)

(2) da152: Processing and preserving of fish and fish products (18 countries)

(3) da153: Processing and preserving of fruit and vegetables (23 countries)

(4) da154: Manufacture of vegetable and animal oils and fats (17 countries)

(5) da155: Manufacture of dairy products (24 countries)

(6) da156: Manufacture of grain mill products, starches and starch products (21 countries)

(7) da157: Manufacture of prepared animal feeds (21 countries)

(8) da158: Manufacture of other food products (24 countries)

(9) da159: Manufacture of beverages (23 countries)

For each of the industries the input distance function is analyzed using stochastic frontier analysis (SFA) and data envelopment analysis (DEA). To estimate the stochastic distance function the Cobb-Douglas functional form is used as an approximation to the true input distance measure. For the DEA model two different assumptions are made on the underlying technology (constant returns to scale (CRS) and variable returns to scale (VRS))[1]. Also, Spearman Rank coefficient is used to compare SFA and DEA scores. Finally, convergence of countries technical efficiency will be evaluated for the four year period under analysis using sigma convergence, which measures the evolution of the standard deviation of the efficiency scores over time.

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[1] Due to space limitations only average yearly results are reproduced here. A complete set of results is available upon request.

3. Results

3.1. Cross-methodology comparison

Average yearly results for the three models are presented in Appendix A (tables A.I, A.II and A.III). These estimations provide some insights about efficiency indices across countries and food industries. Looking at the mean value of technical efficiency predictions for each of the 9 industries (at the bottom of the tables) we observe that efficiency scores based of SFA generally produced lower scores than DEA with CRS or VRS assumptions. Differences come from the treatment that both methodologies have with respect to efficiency. DEA models measure efficiency as the distance of each country activity to the production frontier. Any deviation from the frontier is treated as inefficiency in DEA. The deviation from the best practice frontier in SFA is a residual composed of a term indicating managerial incompetence and a symmetric random error term reflecting omitted variables and measurement errors. So, it is understandable those lower scores for SFA scores.

Efficiency scores based on the CRS assumption generally produced lower scores than the VRS assumption. This is an expected result, since VRS relaxes the assumption that all countries operate at an optimal scale, pulling the frontier to envelop the observations more closely. Some countries that were not efficient under CRS are now 100% efficient. The difference between the two indices indicates rigidities to adjust the size of their industries. This was the case of some big countries such as France and Germany. Germany has a VRS score of almost 1, indicating that is technically very efficient, but the CRS index is only of 0.92, indicative of country food industries inappropriately sized and, therefore, the country is scale inefficient.

The Spearman rank correlation coefficient (*r*) is used to compare the ranking of the efficiency indexes obtained by the different models. Spearman rank coefficient compares the rank order of each variable instead of mean values since cardinal comparisons of values are not meaningful, given the different methodologies[2]. The rank coefficients for the estimated models are presented in Table I. To test whether an observed value of *r* is significantly different from zero, the rank coefficient has a Student t-distribution. Rejection of the null hypothesis in favor of the alternative hypothesis implies that there is a statistically significant relationship between the rankings of the two variables. In most cases (all except two), the coefficient was significant at the 1% level, implying a significant ranking relationship between the indexes calculated by the stochastic and parametric techniques. There is a strong positive correlation between the technical efficiencies estimated by the different models. The correlation between the SFA and the CRS DEA scores is statistically significant in all cases, with values of Spearman Rank coefficient raging between 0.41 and 0.86. Between SFA and VRS there are two cases where the Spearman Rank coefficient is not statistically significant (manufactures of fish products and grain mill and starches), meaning that these two estimation techniques yield different country rankings for the two industries. In the other 7 industries the Rank coefficient is statistically significant with values ranging between 0.56 and 0.72. Comparing the two DEA models, CRS and VRS, we obtain a positive and statistically significant relation for all industries.

In general we do not observe a lot of differences in the technical efficiencies obtained using the various methods. It is difficult to compare absolute figures from SFA and

[2] The coefficient is a non-parametric measure that evaluates how well an arbitrary monotonic function could describe the relationship between two variables without making any assumptions about the frequency distribution of the variables. The raw scores are converted to ranks, and the differences between the ranks of each observation on the two variables are calculated.

DEA, since the estimation technique is different. In order to decide which estimation technique is better, DEA or SFA, Coelli and Perelman (1999) suggest using a combination of the scores obtained from the different methods as a preferred score, by constructing geometric means of the scores for each data point. This idea comes from the time series forecasting literature, which says that the average of the predictions from a number of models will often outperform any one particular model. For that reason, the means of the SFA and CRS predictions and country rankings are tabulated in Table II[3].

3.2. EU food industry combined efficiency

The industry average scores vary from the lowest which corresponds to the manufacture of beverages (0.72) to the highest reached by two food industries: processing and preserving of fish and fish products, and the manufacture of dairy products. These efficiency values indicate that there is room for improvement in the different sectors, an efficiency index of 0.72 means that the European industry of beverages can reduce their use of inputs by 28% and still produce the same amount of output. Efficiency scores reveal how average food industries performs, nevertheless it could be the case that there might be great discrepancies among firms and group of firms.

Among the countries of the EU 15 there are some specializations for food industries with the greatest scores. For example, the production, processing, preserving of meat and meat products has the highest values in Denmark and United Kingdom; fish and fish products are very strong in UK, Germany and Finland; Norway, UK and Austria are very efficient on processing fruits and vegetables. Those examples and many other results show that efficient food industries could be linked to abundant natural resources,

[3] The stochastic frontier estimated in this paper has a CRS orientation. For that reason the geometric mean is calculated using only SFA and DEA scores, both with CRS orientation, and does not include the VRS scores.

but this is not always the case because there are countries in other situations, with large imports of raw materials and very efficient in their transformation.

The most developed countries have usually figures ranging from 0.85 to 0.95 whereas most of the new EU countries have scores from 0.70 to 0.85. The highest overall score has been reached by the United Kingdom, with 0.96, followed by Sweden (0.94). In third place are Denmark, Ireland, and Norway, with an average efficiency of 0.93. UK has ranked in the first and second place for almost all food industries except for the manufacture of prepared animal feeds and dairy products, where it is ranked in 12th and 5th place respectively, which is a good indication of how effective the food industry is in that country. Probably it also shows the great tradition that this country has importing many inputs from different countries and trying to look for the best opportunities to buy commodities from all over the world.

Other big countries, like France and Germany ranking in the 13th and 7th place respectively according to the overall efficiency score, do not have such overall performing food industries. Their scores vary from one to other food industry with greater differences than in UK. It does not prevent from having some firms, on those food industries, at the very top on the European level. As we have seen before much of these inefficiencies are due to inappropriately sized industries. In Germany, the manufacture prepared animal feeds, followed by the manufacture of other food products are the least performing food industries. For France the worst performing industries are the manufacture of meat products (17th place), prepared animal feeds (16th place) and other food products (16th place).

It is rather surprising that both Italy and Spain have low scores for the processing and preserving of fruit and vegetables, as those countries are quite efficient producing fresh fruit and vegetables. It shows poorly structured processed industries for those food products. However, those two countries have the highest values, along with Portugal and Cyprus, for the manufacture of dairy products, which might not be an expected result. Their processing industries have been able to compensate for the lack of competitive natural resources for those commodities.

Among the most recently incorporated countries in the EU, overall scores are significantly lower. However, there are countries with particular food industries being very efficient. This is the case, for example, for manufacture of meat products in Estonia, Latvia and Slovenia; or for fish in Estonia and Latvia; or for fruits and vegetables in the Czech Republic and Slovenia. These results are encouraging for those food industries to compete in the EU market. Food industry inefficiencies in those countries might provide, on the other hand, opportunities for foreign capital to invest and get good returns. It is interesting to note that the two countries with the lowest rankings in most of the industries have not yet joined the EU, Bulgaria and Romania.

3.3. Convergence estimates

Convergence of countries technical efficiency has been evaluated for the four year period under analysis using sigma convergence, which measures the evolution over time of the standard deviation of the efficiency scores, calculated using SFA (Delgado and Alvarez, 2005). The results are presented graphically in figure 1. The period analyzed is short, but is observable a decrease on the standard deviation in almost all industries. The results display that convergence speeds are not similar for all industries, but differences among countries narrowed slightly.

The processing and preserving of fish and fish products is the most homogenous industryr in terms of efficiency among the analyzed countries, even so, this industry efficiency scores are also converging. On the other hand, the most heterogeneous sector is the manufacture of beverages, being also the most inefficient, and it shows the fastest convergence process. The exception to this convergence process is “Manufacture of vegetable and animal oils and fats” (NACE 154), which standard deviation of the efficiency scores increases over time. In this industry, there is not only a divergence between countries, but also a decrease on the overall efficiency scores across time in all countries. It might be a consequence of a changing and unstable productive environment for crops and animal production that can be transformed into oils. In general, all other industries have experienced an efficiency increase during the four year period. The convergence process linked to the average efficiency improvement seems to indicate that those countries that initially had lower scores are improving faster than countries with higher initial efficiency levels.

4. Discussion

Efficiency scores of the food industry across Europe are computed using a multi-input distance function, employing both parametric and non-parametric techniques, in order to provide a crosscheck on the efficiency scores. One of the main conclusions is that the different estimation techniques, DEA and SFA, provide reassuringly similar information on the relative efficiency performance of the 25 countries and 9 food industries considered in the analysis. The correlations between the various sets of technical efficiency predictions are all positive and significant. A multi-technique approach can help to overcome limitations and possible bias of using the results of individual methods by constructing averages of multiple results which may potentially be better than any of the original predictions. The results indicate that, in most cases, the EU-15 countries performed better than recently incorporated countries. This performance gap is particularly evident when comparing to countries such as Romania or Bulgaria that have not yet joined the EU. Then, the food industry competitiveness is higher in the old European member countries than in the new member states. In this context, the food industry in the new member states, although they might have opportunities to get cheaper agricultural commodities with the implementation of the CAP, it has however the challenge ahead to increase competitiveness to achieve the levels of their European partners. Moreover, this lower competitiveness might provide opportunities for foreign capital to invest in those countries to get good returns.

In general, the food industry in the EU-15 can be considered competitive although there is still room for improvement. More research is needed to compare food industries in United States and other developed countries. Moreover, the more competitive food sectors are processing and preserving fish and fish products and the manufacture of dairy products and the less one the manufacture of beverage.

UK shows the highest competitiveness for the food industry as a whole and for all the food industries. Other countries with highly competitive food industry are Ireland and Northern countries (Sweden, Denmark and Norway). However, other big countries like France and Germany present less competitive food industries, for their average performance, and this lower competitiveness is, according to the analysis, mainly due to the inappropriate size of the industry. It is important to remark that countries such as Italy or Spain, that are quite efficient in producing fresh fruits and vegetables, present low efficiency scores for the processing and preserving of those commodities. However, these two countries are very efficient manufacturing dairy products. This result, together with the high competitiveness observed in the UK food industry, suggested that a country could be very competitive producing processed food product, even when they do not produce or are not specialized on producing the raw commodities.

Although the absolute differences in country efficiency levels require further examination, the relative changes over time indicates a convergence process on the efficiency performance. Convergence of the efficiency scores points out that the differences in the food industry competitiveness of the EU countries have reduced over the studied period. The convergence process linked to the average efficiency improvement might reflect that those countries that initially have less competitive food industry show a faster improvement on competitiveness than countries that presented higher competitiveness levels. On the other hand, the most heterogeneous sector is the manufacture of beverages, being also the most inefficient and less competitive showing the fastest convergence process. The exception to this convergence process is the manufacture of vegetable and animal oils and fats, where there is not only a divergence between countries, but also a decrease in the overall efficiency scores across time. It means that the processing of vegetables and animal oils and fats was the sector less competitive and his competitiveness is decreasing over the studied period.

Countries efficiency scores could provide good indicators of the average food industry competitiveness across countries. This information is useful for food companies in order to know where the investment opportunities are, although individual enterprises can overcome the competitive situation existing in a specific food industry. A freer market might imply that a country, which does not have special natural resources for a food industry, could nevertheless be competitive in the manufacturing of food products.

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APPENDIX:

Table A.1. Stochastic Frontier Analysis (SFA) efficiency scores by food industry (average 2000-2003)

	NACE code									
	151	152	153	154	155	156	157	158	159	Total
Austria	0.958	-	0.938	-	0.845	0.965	0.905	0.981	0.753	0.907
Belgium	0.858	-	0.873	0.959	0.925	0.663	0.864	0.803	0.659	0.825
Bulgaria	0.775	0.799	0.605	0.513	0.843	0.752	0.680	0.805	0.616	0.710
Cyprus	-	-	-	0.862	0.990	-	0.878	0.904	0.689	0.865
Czech Rep.	0.824	-	0.804	-	0.828	0.841	0.681	0.839	0.641	0.780
Denmark	0.988	0.894	0.873	-	-	0.969	-	0.933	0.830	0.914
Estonia	0.970	0.966	0.808	-	0.718	-	-	0.889	0.513	0.811
Finland	0.834	0.980	0.779	0.963	0.854	0.891	0.959	0.930	0.615	0.867
France	0.815	0.876	0.796	0.866	0.970	0.896	0.897	0.862	0.671	0.850
Germany	0.925	0.962	0.852	0.935	0.932	0.908	0.919	0.944	0.735	0.901
Hungary	0.807	-	0.710	0.862	0.806	0.861	0.888	0.811	0.680	0.803
Ireland	0.879	0.969	-	-	0.835	0.785	0.930	0.968	0.960	0.904
Italy	0.843	0.851	0.799	0.945	0.987	0.809	0.956	0.884	0.641	0.857
Latvia	0.977	0.962	0.791	-	0.975	-	0.947	0.971	0.790	0.916
Lithuania	0.918	0.841	0.864	-	0.910	0.906	0.987	0.953	0.740	0.890
Netherlands	0.870	0.909	0.834	0.583	0.912	0.902	0.947	0.845	-	0.850
Norway	0.864	0.900	0.982	0.795	0.914	-	0.974	0.966	0.977	0.921
Poland	0.782	-	0.789	-	0.921	0.907	-	0.969	0.931	0.883
Portugal	0.903	0.820	0.845	0.859	0.981	0.831	0.967	0.917	0.574	0.855
Romania	0.682	0.841	0.601	0.698	0.777	0.706	0.752	0.659	0.629	0.705
Slovenia	0.970	-	0.925	0.781	0.819	0.962	0.853	0.961	0.632	0.863
Slovakia	0.729	0.709	0.747	0.821	0.747	0.958	0.738	0.740	0.581	0.752
Spain	0.887	0.885	0.782	0.908	0.981	0.803	0.939	0.921	0.646	0.861
Sweden	0.922	0.964	0.937	0.904	0.961	0.919	-	-	-	0.934
UK	0.984	0.977	0.980	0.973	0.976	0.984	0.941	0.981	0.858	0.962
Ind. average	0.874	0.895	0.822	0.837	0.892	0.868	0.886	0.893	0.711	
# Countries	24	18	23	17	24	21	21	24	23	

Table A.2. Data Envelopment Analysis (DEA) constant returns to scale efficiency scores by food industry (average 2000-2003)

	NACE code									
	151	152	153	154	155	156	157	158	159	Total
Austria	0.968	-	1.000	-	0.912	0.973	0.927	0.944	0.744	0.924
Belgium	0.989	-	0.962	1.000	0.997	1.000	1.000	0.803	0.813	0.946
Bulgaria	0.705	0.777	0.631	0.584	0.798	0.721	0.669	0.666	0.544	0.677
Cyprus	-	-	-	0.964	1.000	-	0.964	0.824	0.689	0.888
Czech Rep.	0.814	-	0.973	-	0.889	0.892	0.655	0.727	0.580	0.790
Denmark	1.000	0.962	0.917	-		1.000	-	0.907	0.864	0.942
Estonia	0.883	0.985	0.770	-	0.754	-	-	0.759	0.511	0.777
Finland	0.848	0.968	0.889	0.974	0.915	0.974	1.000	0.904	0.670	0.905
France	0.902	0.940	0.916	0.843	0.983	0.911	0.854	0.831	0.978	0.907
Germany	0.999	1.000	0.997	0.915	0.982	0.937	0.903	0.884	0.718	0.926
Hungary	0.764	-	0.701	0.880	0.873	0.841	0.856	0.708	0.646	0.784
Ireland	0.966	0.966		-	0.933	0.961	0.945	1.000	1.000	0.967
Italy	0.944	1.000	0.889	0.907	0.999	0.977	0.939	0.861	0.838	0.928
Latvia	0.885	0.980	0.869	-	0.964	-	0.974	0.828	0.793	0.899
Lithuania	0.823	0.857	0.869	-	0.895	0.867	0.983	0.780	0.674	0.843
Netherlands	1.000	1.000	0.929	0.793	1.000	0.969	0.986	0.827	-	0.938
Norway	0.924	0.968	0.999	0.815	0.955	-	0.996	0.926	1.000	0.948
Poland	0.765	-	0.892	-	0.914	0.886	-	0.848	0.855	0.860
Portugal	0.865	0.807	0.807	0.857	0.994	0.835	0.956	0.828	0.553	0.833
Romania	0.630	0.832	0.629	0.753	0.716	0.656	0.743	0.550	0.546	0.673
Slovenia	0.907	-	0.908	0.873	0.892	0.989	0.978	0.881	0.624	0.882
Slovakia	0.695	0.715	0.732	0.900	0.797	0.932	0.739	0.645	0.524	0.742
Spain	0.904	0.893	0.827	0.848	0.990	0.898	0.886	0.860	0.662	0.863
Sweden	0.945	0.960	0.964	0.912	0.974	0.957	-	-	-	0.952
UK	0.985	1.000	1.000	0.982	0.960	0.997	0.887	0.932	0.830	0.952
Ind. average	0.880	0.923	0.872	0.870	0.920	0.913	0.897	0.822	0.724	
# Countries	24	18	23	17	24	21	21	24	23	

Table A.3. Data Envelopment Analysis (DEA) variable returns to scale efficiency scores by food industry (average 2000-2003)

	NACE code									
	151	152	153	154	155	156	157	158	159	Total
Austria	0.977	-	1.000		0.925	0.986	0.934	0.946	0.758	0.932
Belgium	0.992	-	1.000	1.000	0.997	1.000	1.000	0.847	0.837	0.959
Bulgaria	0.732	1.000	0.641	0.606	1.000	0.744	0.678	0.718	0.640	0.751
Cyprus	-	-	-	1.000	1.000	-	0.981	1.000	1.000	0.996
Czech Rep.	0.825	-	0.984	-	0.897	0.906	0.700	0.739	0.589	0.806
Denmark	1.000	0.963	0.919	-	-	1.000	-	0.911	0.886	0.946
Estonia	1.000	0.992	1.000	-	0.967	-	-	1.000	1.000	0.993
Finland	0.874	1.000	0.900	0.978	0.919	0.977	1.000	0.915	0.877	0.938
France	1.000	1.000	0.938	0.874	1.000	1.000	1.000	1.000	1.000	0.979
Germany	1.000	1.000	1.000	1.000	1.000	1.000	0.997	1.000	1.000	1.000
Hungary	0.768	-	0.703	0.906	0.883	0.845	0.880	0.723	0.679	0.798
Ireland	0.975	0.973	-	-	0.939	1.000	0.953	1.000	1.000	0.977
Italy	1.000	1.000	0.922	0.991	1.000	1.000	0.996	0.996	0.919	0.981
Latvia	0.950	0.981	1.000	-	0.981	-	0.990	0.961	1.000	0.980
Lithuania	0.922	0.885	1.000	-	0.918	1.000	1.000	0.934	0.969	0.954
Netherlands	1.000	1.000	0.981	0.883	1.000	0.999	1.000	0.906	-	0.971
Norway	0.934	0.992	1.000	0.824	0.958	-	1.000	0.945	1.000	0.957
Poland	0.767	-	0.893	-	0.925	0.918	-	0.849	0.950	0.883
Portugal	0.871	0.814	0.817	0.877	0.998	0.864	0.984	0.835	0.564	0.847
Romania	0.637	0.956	0.642	0.769	0.758	0.666	0.758	0.565	0.554	0.701
Slovenia	0.935	-	0.928	1.000	0.984	1.000	1.000	0.942	0.870	0.957
Slovakia	0.726	0.970	0.802	0.919	0.831	0.950	0.750	0.689	0.594	0.804
Spain	0.955	0.986	0.851	0.983	0.994	0.965	1.000	0.904	0.840	0.942
Sweden	0.958	0.967	0.971	0.929	0.980	0.967	-	-	-	0.962
UK	1.000	1.000	1.000	0.982	0.971	1.000	0.968	1.000	1.000	0.991
Ind. average	0.908	0.971	0.908	0.913	0.951	0.942	0.932	0.888	0.849	
# Countries	24	18	23	17	24	21	21	24	23	

Figure 1. Convergence of Stochastic Frontier Analysis (SFA) efficiency scores

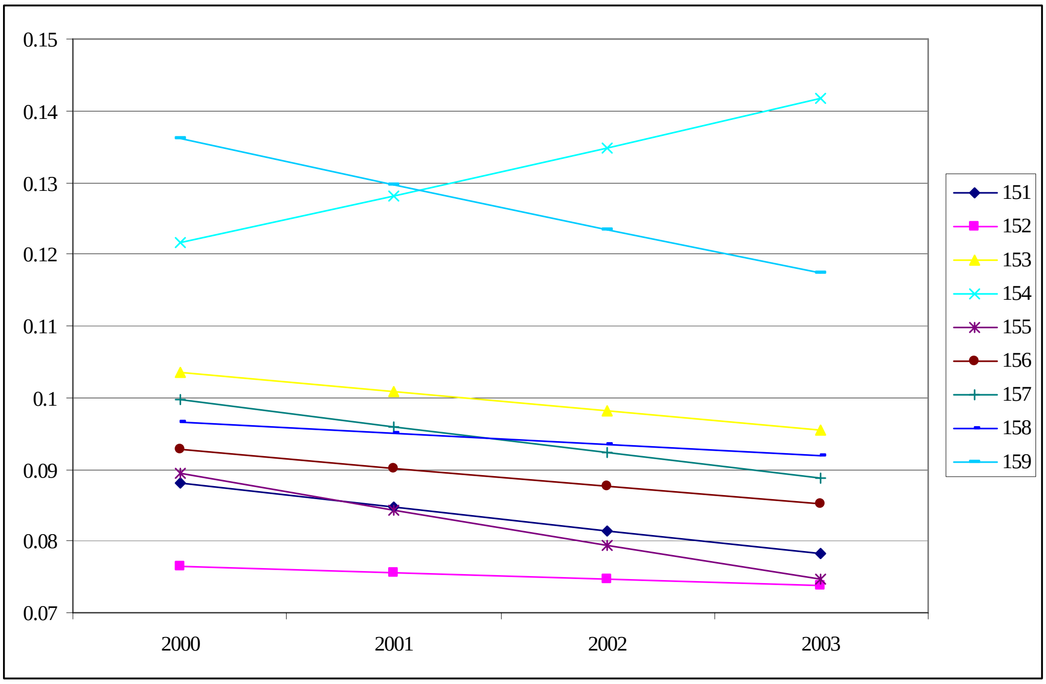

Table 1. Spearman rank coefficients

	SFA	CRS	VRS	SFA	CRS	VRS	SFA	CRS	VRS
	Meat products			*Fish products*			*Fruit and vegetables*		
SFA	1			1			1		
CRS	0.65	1		0.71	1		0.80	1	
VRS	0.62	0.86	1	0.33*	0.59	1	0.72	0.69	1
	Oils and fats			*Dairy products*			*Grain mill, and starches*		
SFA	1			1			1		
CRS	0.83	1		0.86	1		0.41	1	
VRS	0.60	0.77	1	0.65	0.73	1	0.34*	0.75	1
	Animal feeds			*Other food products*			*Beverages*		
SFA	1			1			1		
CRS	0.62	1		0.79	1		0.82	1	
VRS	0.59	0.73	1	0.59	0.61	1	0.56	0.61	1

* not significant at 1% level

Table 2. Geometric mean of Stochastic Frontier Analysis (SFA) and constant returns to scale Data Envelopment Analysis (CRS-DEA) and country rankings (average 2000-2003)

	151		152		153		154		155		156		157		158		159		TOTAL	
	Eff	Ra	Eff	Ra	Eff	Ra	Eff	Ra	Eff	Ra	Eff	Ra	Eff	Ra	Eff	Ra	Eff	Ra	Eff	Ra
AUS	0.96	3	-	-	0.97	3	-	-	0.88	17	0.97	4	0.92	11	0.96	2	0.75	8	0.92	6
BEL	0.92	11	-	-	0.92	7	0.98	1	0.96	9	0.81	19	0.93	9	0.80	19	0.73	10	0.88	12
BUL	0.74	22	0.79	17	0.62	22	0.55	17	0.82	21	0.74	20	0.67	20	0.73	22	0.58	20	0.69	24
CYP	-	-	-	-	-	-	0.91	6	0.99	1	-	-	0.92	10	0.86	14	0.69	13	0.88	14
CZR	0.82	19	-	-	0.88	9	-	-	0.86	18	0.87	15	0.67	21	0.78	20	0.61	18	0.78	22
DEN	0.99	1	0.93	10	0.89	8	-	-			0.98	2	-	-	0.92	5	0.85	4	0.93	5
EST	0.93	9	0.98	3	0.79	19	-	-	0.74	24	-	-	-	-	0.82	18	0.51	23	0.79	20
FIN	0.84	18	0.97	4	0.83	15	0.97	3	0.88	15	0.93	8	0.98	3	0.92	7	0.64	16	0.89	11
FRA	0.86	17	0.91	12	0.85	12	0.85	12	0.98	5	0.90	10	0.88	16	0.85	16	0.81	6	0.88	13
GER	0.96	4	0.98	2	0.92	5	0.93	5	0.96	10	0.92	9	0.91	15	0.91	8	0.73	11	0.91	7
HUN	0.79	20	-	-	0.71	21	0.87	9	0.84	20	0.85	16	0.87	17	0.76	21	0.66	14	0.79	21
IRE	0.92	10	0.97	6	-	-	-	-	0.88	16	0.87	14	0.94	8	0.98	1	0.98	2	0.93	4
ITA	0.89	14	0.92	11	0.84	13	0.93	4	0.99	2	0.89	12	0.95	7	0.87	12	0.73	9	0.89	10
LAT	0.93	8	0.97	5	0.83	16	-	-	0.97	6	-	-	0.96	6	0.90	10	0.79	7	0.91	8
LIT	0.87	16	0.85	14	0.87	11	-	-	0.90	14	0.89	13	0.98	2	0.86	15	0.71	12	0.87	17
NET	0.93	7	0.95	8	0.88	10	0.68	16	0.96	11	0.93	7	0.97	4	0.84	17	-	-	0.89	9
NOR	0.89	13	0.93	9	0.99	1	0.80	14	0.93	12	-	-	0.99	1	0.95	4	0.99	1	0.93	3
POL	0.77	21	-	-	0.84	14	-	-	0.92	13	0.90	11	-	-	0.91	9	0.89	3	0.87	16
POR	0.88	15	0.81	16	0.83	17	0.86	11	0.99	3	0.83	18	0.96	5	0.87	13	0.56	21	0.84	19
ROM	0.66	24	0.84	15	0.61	23	0.72	15	0.75	23	0.68	21	0.75	18	0.60	24	0.59	19	0.69	25
SLO	0.94	5	-	-	0.92	6	0.83	13	0.85	19	0.98	3	0.91	13	0.92	6	0.63	17	0.87	15
SLVK	0.71	23	0.71	18	0.74	20	0.86	10	0.77	22	0.94	5	0.74	19	0.69	23	0.55	22	0.75	23
SPA	0.90	12	0.89	13	0.80	18	0.88	8	0.99	4	0.85	17	0.91	14	0.89	11	0.65	15	0.86	18
SWE	0.93	6	0.96	7	0.95	4	0.91	7	0.97	8	0.94	6	-	-	-	-	-	-	0.94	2
UK	0.98	2	0.99	1	0.99	2	0.98	2	0.97	7	0.99	1	0.91	12	0.96	3	0.84	5	0.96	1
Avera.	0.88		0.91		0.85		0.85		0.91		0.89		0.89		0.86		0.72		0.86	

Eff= geometric mean of the efficiency scores
Ra= country ranking