Comparative analysis of technical efficiency in European agriculture

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Paper prepared for presentation at the EAAE 2011 Congress
Change and Uncertainty
Challenges for Agriculture,
Food and Natural Resources

August 30 to September 2, 2011
ETH Zurich, Zurich, Switzerland

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ABSTRACT

Technical efficiency has long been analysed as a measure of farm performance, however most studies are restricted to a single country case. This paper presents a comparative analysis of field crop and dairy farm performance across eight EU countries, including two New Member States (NMS), focusing on long run stability and mobility patterns. The main research question is how relative performance of farms fluctuates over time, i.e. whether poorly performing farms remain always inefficient whilst some farms are always very efficient. Results show that on average 60% of farms maintain their efficiency ranking in two consecutive years, whilst 20% improve and 20% worsen their positions, for all countries. Due to the unstable economic conditions, farms in NMS are more mobile than those in EU15.

KEYWORDS: Farm technical efficiency, SFA, FADN, stability analysis

JEL CLASSIFICATION: P52, Q12

1. INTRODUCTION

The technical efficiency refers to the situation where it is impossible for a farm to produce more with given technology. There are two possibilities for farmers. First, produce larger output using the same inputs, second, produce the same output with less amounts of inputs. In practice, the research and policy interests are focusing on the relative position in terms of efficiency of particular farm with respect to others. Consequently, the technical efficiency can be described by the relationship between observed output and some ideal or potential production. There is wealth of methodological and empirical literature focusing on the issues in efficiency and productivity (standard theoretical references Coelli et al., 2005; Kumbhakar and Lovell, 2000; while comprehensive overview on empirical research Bravo-Ureta et al. 2007). There exist two main approaches developed over time for analysing technical efficiency in agriculture. (1) The construction of a nonparametric piecewise linear frontier using linear programming method known as data envelopment analysis (DEA); (2) the estimation of a parametric production function using stochastic frontier analysis (SFA). We apply stochastic frontier analysis to measure efficiency. In addition, most studies focus on a single country's agricultural sector, thus the comparative analysis of the technical efficiency is rather scarce (see recent exceptions Barnes et al 2010, and Zhou and Lansink 2010). More importantly, easier availability for research of farm level data, namely FADN data in the EU may provide interesting insights for policy makers on farm level technical efficiency in order to develop more targeted policy, thus improving efficiency in European agriculture.

The aim of this paper is to present and analyse various efficiency indicators for some EU countries including Belgium, Estonia, France, Germany, Hungary, Italy, The Netherlands and Sweden. The availability of long period datasets between 1990 and 2006, allow us to concentrate on the long time trends in technical efficiency especially in Old Member States. This study is the first which may provide a comprehensive overview on the development in farm level efficiency across eight European countries.

The rest of this paper is organised as follows. Section 2 presents a brief review on the methodology including stochastic frontier analysis and stability approaches. Section 3 describes the datasets and provides some descriptive statistics on agricultural structures. Section 4 presents the main results of the analysis in two steps. First we outline the results based on the SFA approach. Second, we present stability analysis. Finally the last chapter summarizes main results of the paper and concludes.

2. METHODOLOGY

2.1. Stochastic Frontier Analysis

Within the parametric approaches, the Stochastic Frontier Analysis, (SFA) is commonly used. *Aigner at al. (1977)* and *Meeusen and Van den Broeck (1977)* have simultaneously yet independently developed the use of SFA in efficiency analysis.

The main idea is to decompose the error term of the production function into two components, one pure random term (v_i) accounting for measurement errors and effects that can not be influenced by the firm such as weather, trade issues, access to materials, and a non-negative one, measuring the technical inefficiency, i.e. the systematic departures from the frontier (u_i):

$$Y_i = f(x_i)\exp(v_i - u_i) \qquad \text{or, equivalently:} \qquad (1)$$

$$\ln(Y)_i = \beta x_i + v_i - u_i)$$

where Y_i is the output of the i^{th} firm, x_i a (k+1) vector of inputs used in the production, $f(\cdot)$ the production function, u_i and v_i the error terms explained above, and finally, β a (k+1) column vector of parameters to be estimated. The output orientated technical efficiency, (TE) is actually the ratio between the observed output of firm i to the frontier, i.e. the maximum possible output using the same input mix x_i.

Arithmetically, technical efficiency is equivalent with:

$$TE_i = \frac{Y_i}{Y_i^*} = \frac{\exp(x_i\beta + v_i - u_i)}{\exp(x_i\beta + v_i)} = \exp(-u_i),\ 0 \le TE_i \le 1. \qquad (2)$$

Contrary to the non-parametric DEA approach, where all technical efficiency scores are located on, or below the efficient frontier (see below), in SFA they are allowed to be above the frontier, if the random error v is larger that the non-negative u.

Applying SFA methods requires distributional and functional form assumptions. First, because only the $w_i = v_i - u_i$ error term can be observed, one needs to have specific assumptions about the distribution of the composing error terms. The random term v_i, is usually assumed to be identically and independently distributed drawn from the normal distribution, $N(0, \sigma_v^2)$, independent of u_i. There are a number of possible assumptions regarding the distribution of the non-negative error term u_i associated with technical inefficiency. However most often it is considered to be identically distributed as a half normal random variable, $N^+(0, \sigma_u^2)$ or a normal variable truncated from below zero, $N^+(\mu, \sigma_u^2)$.

Second, being a parametric approach, we need to specify the underlying functional form of the Data Generating Process, DGP. There are a number of possible functional form specifications available, however most studies employ either Cobb-Douglas (CD):

$$f(x_i) = e^{\beta_0} \prod_{k=1}^{K} x_{ik}^{\beta_k} \qquad (3)$$

or TRANSLOG (TL) specification:

$$\ln f(x_i) = \sum_{k=1}^{K} \beta_k \ln x_{ik} + \frac{1}{2} \sum_{k=1}^{K} \sum_{j=1}^{K} \beta_{kj} \ln x_{ik} \ln x_{jk}\ . \qquad (4)$$

Because the two models are nested, it is possible to test the correct functional form by a Likelihood Ratio, LR test. The TL is a more flexible functional form, whilst the CD restricts the elasticities of substitution to 1. The model could be estimated either with Corrected

Ordinary Least Squares, COLS or Maximum Likelihood, ML. With the availability of computer software, the estimation by ML became less computationally demanding, and the ML estimator was found to be significantly better than COLS (*Coelli et al.,1997*).

With panel data, TE can be chosen to be time invariant, or to vary systematically with time. To incorporate time effects, *Battese and Coelli (1992)* define the non-negative error term as exponential function of time:

$$u_{it} = \exp[(-\eta(t-T)]u_i \tag{5}$$

where t is the actual period, T the final period, and η a parameter to be estimated. TE either increases (η>0), decreases (η<0) or it is constant over time, i.e. invariant (η=0). LR tests can be applied to test the inclusion of time in the model. Since TE is allowed to vary, the question arise what determines the changes of TE scores. Early studies applied a two-stage estimation procedure, first determining the inefficiency scores, and then, in a second stage regressing TE scores upon a number of firm specific variables assumed to explain changes in inefficiency scores. Some authors however showed that conflicting assumptions are needed for the two different estimation stages. In the first stage, the error term representing inefficiency effects, are assumed to be independently and identically distributed, whilst in the second stage they are assumed to be function of firm specific variables explaining inefficiency, i.e. they are not independently distributed (*Curtiss, 2002*). *Battese and Coelli (1995)* proposed a one stage procedure where firm specific variables are used to explain the predicted inefficiencies within the SFA model. The explanatory variables are related to the firm specific mean μ of the non-negative error term u_i:

$$\mu_i = \sum_j \delta_j z_{ij} \tag{6}$$

where μ_i is the i^{th} firm-specific mean of the non-negative error term; δ_j are parameters to be estimated; z_{ij} are i^{th} firm-specific explanatory variables.

Using cross-section or panel data may often lead to heteroscedasticity in the residuals. With heteroscedastic residuals, OLS estimates remain unbiased but no longer efficient. In frontier models however, the consequences of heteroscedasticity are much more severe, as the frontier changes when the dispersion increases. *Caudill et al. (1995)* introduced a model which incorporates heteroscedasticity into the estimation. That is done by modelling the relationship between the variables responsible for heteroscedasticity and the distribution parameter σ_u:

$$\sigma_{ui} = \exp(\sum_j x_{ij}\rho_j) \tag{7}$$

where x_{ij} are the j^{th} input of the i^{th} farm, assumed to be responsible for heteroscedasticity, and ρ_j a parameter to be estimated.

Within SFA approach it is possible to test whether any form of stochastic frontier production function is required or the OLS estimation is appropriate using a LR test. Using the parameterisation of *Battese and Cora (1977)*, define γ, the share of deviation from the frontier that is due to inefficiency:

$$\gamma = \frac{\sigma_u^2}{\sigma_v^2 + \sigma_u^2} \tag{8}$$

where σ^2_v is the variance of the v and σ^2_u the variance of the u error term.

It should be noted however, that the test statistic has a ‘mixed’ chi square distribution, with critical values tabulated in *Kodde and Palm (1996)*.

2.2. Stability Analysis

Efficiency scores as such, do not reveal much about the fluctuation of farms' relative performance. From policy point of view however, it is an interesting question whether low performing farms are always inefficient and vice versa, i.e. farms with higher TE scores are efficient throughout the period. Policy relevance is given by the fact that chronically lower performing farms may be targeted with specific measures in order to improve their efficiency scores. With large panel datasets however, due to sample attrition it is not feasible to follow the TE scores of given farms through longer time periods, therefore comparisons between consecutive years were done. We follow the stability analysis methodology outlined by Barnes et al. (2010). Yearly farm TE scores were classified by terciles, then transition matrices linking two consecutive years were constructed, that indicate whether the considered farm remained in the same tercile, or its relative position has worsened, or contrary, improved.

The degree of mobility in patterns of SFA scores can be summarised using indices of mobility. These formally evaluate the degree of mobility throughout the entire distribution of SFA scores and facilitate direct cross-country comparisons. The first of these indices (M_1, following Shorrocks, 1978) evaluates the trace (tr) of the transition probability matrix. This index thus directly captures the relative magnitude of diagonal and off-diagonal terms, and can be shown to equal the inverse of the harmonic mean of the expected duration of remaining in a given cell.

$$M_1 = \frac{K - tr(P)}{K - 1} \tag{9}$$

where K is the number of cells, and P is the transition probability matrix.

The second index (M_2, after Shorrocks, 1978 and Geweke et al., 1986) evaluates the determinant (det) of the transition probability matrix.

$$M_2 = 1 - \left|\det(P)\right| . \tag{10}$$

In both indices, a higher value indicates greater mobility, with a value of zero indicating perfect immobility.

3. DATA

We use the EU FADN data. Two sectors were considered, based on the Type of Farming (TF) variables A28 (one digit TF) and A29 (two digits TF): field crop farms (TF1) and dairy farms (TF41). Data source is the FADN database from 1990 to the latest available year (2006) in case of "old" Member States and 2004–2006 for "new" Member States. Inconsistent data and outliers were removed from the initial datasets.

Table 1. Descriptive statistics and concentration index of field crop farms (UAA)

	Field Crop	**Utilised Agricultural Area**		
	start period		**end period**	
	mean	**Gini coefficient**	**mean**	**Gini coefficient**
Belgium	54.00	0.2975	73.87	0.3159
Estonia	230.11	0.4754	240.27	0.4824
France	80.89	0.3436	135.88	0.3323
Germany	47.11	0.3501	252.02	0.6358
Hungary	255.45	0.6671	240.05	0.6360
Italy	19.61	0.5081	50.96	0.6503
Netherlands	62.34	0.3220	82.81	0.3684
Sweden	83.61	0.2939	120.19	0.4515

Source: authors' calculations

Tables 1 and 2 show that an obvious concentration process happened in all analysed countries during the period. With the exception of Hungary, sample means of farm size for all countries do increase regardless of the sector. In some countries, average sample mean increased dramatically (e.g. field crop farm size in Germany[1] increased fivefold, Italian field crop and dairy farm sizes trebled, Swedish, French field crop farm sizes doubled). In both tables the second column for both the starting and end period presents the Gini concentration index. Generally the concentration index also increases between the start and end periods, but by far not as dramatically as farm size means. In Belgium, despite the increasing sample size mean of dairy farms, the concentration index actually decreased. The highest sample size means and concentration indices are reported for the New Member States, Hungary and Estonia. With the exception of these two countries however, interestingly, a higher sample size mean does not translate into a higher concentration index.

Table 2. Descriptive statistics and concentration index of dairy farms (livestock units)

	Milk	**Livestock unit**		
	Starting period		**End period**	
	mean	**Gini coefficient**	**mean**	**Gini coefficient**
Belgium	83.59	0.2818	95.94	0.2510
Estonia	84.53	0.5913	97.42	0.5976
France	60.55	0.2546	90.32	0.2940
Germany	64.44	0.2740	136.58	0.4993
Hungary	234.69	0.6755	222.83	0.6867
Italy	35.54	0.4623	100.11	0.5491
Netherlands	106.99	0.2967	127.80	0.3216
Sweden	43.86	0.2795	80.22	0.4274

Source: authors' calculations

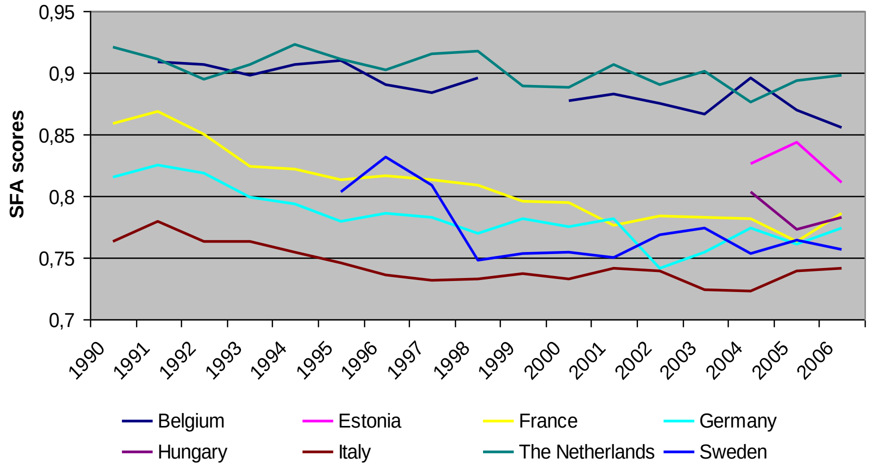
[1] This is mostly due to the effects of the German reunification process, by the inclusion of the large scale former GDR state owned agricultural holdings in the sample.

4. Results

4.1. Development of farm efficiency

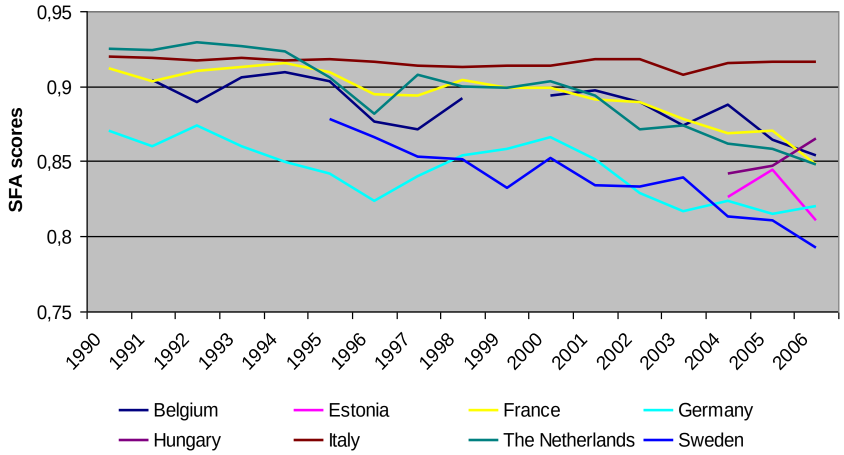
Notable exceptions are Italian dairy farms, which are located in the top of SFA estimations (figure 1). Results are plausible, when mean technical efficiency scores are computed they are largely in line with results obtained by previous studies.

Figure 1. Technical efficiency scores for field crop farms



Some examples confirm this. Zhu and Oude Lansink (2010) employ the longest time-span in their research, and focus on several of the countries represented in this deliverable, this paper may be used as a benchmark to assess our results. For German crop farms, average TE score 0.78 (SFA) computed in this study. Brümmer et al. (2002) report an average TE score of 0.95 for specialised German (Schleswig-Holstein) dairy farms, against 0.84 obtained in this paper, also using parametric methods. For the Netherlands, Zhu and Oude Lansink (2010) report a mean TE score of 0.76, versus 0.90 (SFA). For Dutch dairy farms, Brümmer et al. (2002) present an average TE score of 0.89, we have obtained 0.88 (SFA). Swedish crop farms average TE score was estimated to be 0.71, estimations using same method within this deliverable report 0.77. Barnes et al. (2010) obtained an average TE score of 0.76 using SFA, comparable with 0.74 estimated in this paper with the same method.

Figure 2. Technical efficiency scores for dairy farms



With simple visual inspection of the efficiency estimation figures is difficult to determine whether on long run average per country efficiency scores increase or decrease. We have therefore analysed this issue econometrically by regressing with OLS the TE scores for each sector and each country (for all years pooled together) on a single explanatory variable: the time trend. Table 3 presents the estimated coefficients of per country regressions of efficiency scores on an intercept and time trend as explanatory variable.

Table 3. OLS regression of efficiency scores on a time trend; coefficients' value and significance for the time trend in each country's and TF's regression

	Field Crop	**Dairy**
Belgium	-0.003***	-0.002***
France	-0.007***	-0.004***
Germany	-0.005***	-0.003***
Italy	-0.003***	-0.001**
Netherlands	-0.002***	-0.005*
Sweden	-0.005**	-0.007***

Note: ***, **, * significant on 1, 5 and 10% respectively.
Source: authors' calculations

Significant coefficients are small and negative across regressions, suggesting a decreasing average technical efficiency score for each country and sector included in the analysis. The regressions were not performed for New Member States since their sample covers only 3 years.

4.2. Stability Analysis

Following the technique outlined in the methodology section, we performed the stability analysis for Belgium, Estonia, France, Germany, Hungary, Italy, The Netherlands and Sweden respectively. Our findings suggests a surprising stability of results across countries and sectors over time. Table 4 presents the mean values of the percentage of farms in consecutive years that remain in the same tercile, along those increasing or decreasing their respective terciles.

Table 4. Stability analysis results: percentage of farms in the same tercile during two consecutive years (averages for each country and sector)

	Field Crop			**Dairy**		
	increase	**remain**	**decrease**	**increase**	**remain**	**decrease**
Belgium	0.20	0.61	0.19	0.16	0.66	0.17
Estonia	0.26	0.46	0.28	0.28	0.46	0.26
France	0.19	0.61	0.20	0.20	0.59	0.20
Germany	0.20	0.61	0.19	0.21	0.59	0.20
Hungary	0.26	0.48	0.26	0.26	0.44	0.29
Italy	0.20	0.59	0.21	0.20	0.58	0.22
Netherlands	0.20	0.58	0.21	0.17	0.65	0.18
Sweden	0.18	0.65	0.17	0.21	0.58	0.21

Source: authors' calculations

As suggested earlier, results are surprisingly stable: about 60% of all farms remain in the same tercile two consecutive years, whilst about 15-20% of farms decrease and increase their performance moving down or up a tercile. Results obtained in this section are completely in line with those of Barnes et al. (2010) for crop and dairy farming in England, Scotland, Wales and Northern Ireland.

Table 5. Average change in technical efficiencies for field crop farms depending on their tercile movement

	Belgium	Estonia	France	Germany	Hungary	Italy	Netherlands	Sweden
				Farms remaining each year				
tercile 1	0.224	0.150	0.222	0.243	0.173	0.211	0.226	0.226
tercile 2	0.174	0.133	0.164	0.169	0.134	0.160	0.155	0.181
tercile 3	0.208	0.173	0.222	0.202	0.171	0.215	0.201	0.240
				Farms increasing each year				
tercile 2-1	0.081	0.093	0.082	0.083	0.100	0.089	0.084	0.078
tercile 3-1	0.030	0.058	0.022	0.025	0.057	0.031	0.026	0.017
tercile 3-2	0.091	0.115	0.089	0.084	0.103	0.083	0.094	0.083
				Farms decreasing each year				
tercile 1-2	0.076	0.102	0.086	0.088	0.103	0.091	0.087	0.082
tercile 1-3	0.035	0.053	0.023	0.022	0.060	0.031	0.030	0.013
tercile 2-3	0.082	0.124	0.089	0.084	0.099	0.089	0.097	0.081

Source: authors' calculations

On average, 15% (Estonia) to 24% (Germany) of field crop farms remained in the top tercile each year, 13% (Estonia and Hungary) to 17% (Belgium, Germany) in the middle tercile and 17% (Estonia, Hungary) to 22% (France) in the lower tercile (table 5). It is probably more interesting the percentage of farms that changed their terciles over the year. An average of 10% (France, Germany) to 15% (Estonia, Hungary) improved their performance by shifting into a higher (2 to 1 or 3 to 1) tercile, whilst almost the same, on average 10% (France) to 16% (Hungary) fell from the top or middle tercile to the lowest.

Table 6. Average change in technical efficiencies for dairy farms depending on their tercile movement

	Belgium	Estonia	France	Germany	Hungary	Italy	Netherlands	Sweden
				Farms remaining each year				
tercile 1	0.244	0.161	0.090	0.205	0.140	0.221	0.239	0.213
tercile 2	0.179	0.127	0.060	0.159	0.104	0.157	0.178	0.160
tercile 3	0.240	0.172	0.105	0.225	0.201	0.200	0.236	0.209
				Farms increasing each year				
tercile 2-1	0.072	0.109	0.086	0.086	0.140	0.096	0.074	0.079
tercile 3-1	0.015	0.071	0.027	0.025	0.050	0.028	0.015	0.030
tercile 3-2	0.077	0.105	0.094	0.090	0.073	0.084	0.078	0.096
				Farms decreasing each year				
tercile 1-2	0.077	0.090	0.086	0.092	0.161	0.095	0.081	0.082
tercile 1-3	0.012	0.060	0.026	0.027	0.029	0.033	0.015	0.032
tercile 2-3	0.085	0.105	0.092	0.092	0.102	0.086	0.084	0.099

Source: authors' calculations

For dairy farm analysis (table 6), an average of 9% (France) to 24% (Belgium) remained in the top, 6% (France) to 18% (Belgium) in the middle and 10% (France) to 24% (Belgium) in the lower tercile over one year period. As for field crop farms, it is more of an interest to comment the percentage of farms improving or worsening their positions over the period. On

average 9% (Belgium) to 19% (Estonia, Hungary) improved their technical efficiency scores by moving up one or two terciles, whilst a similar number, 9% (Belgium) to 19% (Hungary) fell from the middle or highest tercile to the lowest. It is interesting to note, that for both field crop and dairy farms, New Member States (Estonia and Hungary) register the highest average percentage of farms either dramatically increasing or decreasing their terciles, suggesting a highly unstable yearly performance. These countries also register the lowest percentages of farms that are stable in the same tercile during the year.
The mean of yearly mobility indexes, M1 and M2 (see equations 9 and 10), for the Old Member States are presented in table 7. For both indices a higher value indicates greater mobility, whilst a value close to zero indicates perfect immobility.

Table 7. Means of M1 and M2 mobility indices for field crop and dairy farms

	Field Crop		**Dairy**	
	M1	**M2**	**M1**	**M2**
Belgium	0.59	0.82	0.50	0.79
Estonia	0.81	0.99	0.81	0.98
France	0.59	0.86	0.61	0.89
Germany	0.58	0.85	0.62	0.89
Hungary	0.78	0.97	0.83	0.97
Italy	0.62	0.88	0.63	0.89
Netherlands	0.63	0.86	0.52	0.80
Sweden	0.52	0.81	0.63	0.87

Source: authors' calculations

Index means are remarkably similar across countries in this research. It is important to notice, that the M2 index ranks countries in the same way as M1 does, implying consistency of results. M1 ranges from 0.52 to 0.63 (0.50 to 0.63) for field crop (dairy) farms, and M2 from 0.81 to 0.88 (0.79 to 0.89) for field crop (dairy) farms indicating a similar degree of mobility for the Old Member States represented here. M1 and M2 indices are significantly higher for New Member States (Estonia and Hungary). M2 reaches 0.97 and 0.99 for both sectors in Hungary and Estonia, suggesting higher mobility of SFA scores throughout the entire distribution. For field crop farming, the lowest mobility scores are recorded for Sweden, whilst for dairy farms in Belgium and Netherlands.

5. CONCLUSIONS

The aim of this paper is to present and analyse various efficiency indicators for countries included in the FACEPA project, Belgium, Estonia, France, Germany, Hungary, Italy, The Netherlands and Sweden. The availability of long period datasets between 1990 and 2006, allows us to concentrate on the long time trends in technical efficiency especially in Old Member States. This study is the first which may provide a comprehensive overview on the development in farm level efficiency across eight European countries.
Our main results are following. Generally, all countries have relatively high levels of mean efficiency ranging from 0.72 to 0.92 for both field crops and dairy farms. Interestingly majority of countries have better performance in dairy sectors in terms of higher levels of mean efficiency than in field crop production. This suggests that larger heterogeneity in terms of agricultural practices may be present in crop farming than in dairy farming. This is contrary to the intuition that livestock farming, which requires more human input than crop farming, would present a larger heterogeneity of human practices (this assumption was for example put forward by Curtiss 2000). However, an explanation may be that crop farming is more affected

by land quality and climate conditions than livestock farming. Latruffe et al. (2009) have for example provided evidence of the role of climate conditions on farms' technical efficiency. Input quality is not taken into account within our analysis, as it is impossible to find equivalent proxy across all countries. Therefore, lower efficiency in field crop sector than in dairy sector may in fact be due to different land quality, which may affect farms' performance more than labour quality for example. A slightly decreasing trend of efficiency may be observed for all countries. Technical Efficiency estimates are largely in line with those obtained by previous studies.

We investigate the issue of how relative performance of farms fluctuates in terms of technical efficiency over time. We may hypothesise that many poorly performing farms remain inefficient over time and some farmers are performing always very efficiently. We can identify farms which are usually at the bottom or top of the efficiency ranking. However, the FADN data has an inherent problem for long time period analysis arising from its rotated panel nature, namely that not all the farms are observed for the whole period. So we need to calculate transition matrices in each consecutive year. Surprisingly stability analysis revealed that in average 60% of farms maintain their efficiency ranking in two consecutive years, whilst 20% improve and 20% worsen their positions for all countries. However, these ratios slightly fluctuate around these values for one year to next year. Mobility analysis ranks countries according to the mobility of SFA scores within the distribution. Farms in New Member States are more mobile than those in EU15. This may be due to the unstable economic conditions of farms in these countries, where e.g. inputs access is not always secured or is costly.

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