Technical efficiency and determinants of mobility patterns in European agriculture

Zoltán Bakucs, Imre Ferto, Laure Latruffe and Yann Desjeux

Abstract: European agriculture has undergone considerable structural changes in the last two decades, with a decreasing number of farms and increasing farm size. One important question is whether these changes have been translated into improvements in technical efficiency. The paper provides a comparative analysis of farm technical efficiency in eight EU member states. More specifically, the authors focus on the relative performance fluctuation over time – namely, whether poorly performing farms always remain inefficient whilst some farms are always efficient. The most striking results are as follows. First, there is a remarkable robustness of farm efficiency stability across countries: on average, 60% of farms maintain their efficiency ranking in two consecutive years, while 20% improve and 20% worsen their positions. Second, there is a clear difference between the mobility indicators with respect to farm technical efficiency ranking between the EU15 and the new member states (NMS) included in the study. Due to unstable economic conditions, farms in NMS are more mobile than those in the EU15. Finally, using second-stage regression of mobility scores on a set of farm-specific explanatory variables, some explanations of the mobility patterns are offered.

Keywords: farm efficiency; stability analysis; stochastic frontier analysis (SFA); Farm Accountancy Data Network (FADN)

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The term ‘technical efficiency’ refers to a situation in which it is impossible for a farm to produce more with a given technology. There are two possibilities for farmers – either to produce a higher output using the same amount of inputs, or to produce the same output but with fewer inputs. In practice, research and policy interests focus on the relative position in terms of efficiency of a particular farm with respect to others. Consequently, technical efficiency can be described by the relationship between the observed output and some ideal or potential production. There is a wealth of methodological and empirical literature focusing on the issues of efficiency and productivity (standard theoretical references – Coelli et al, 2005; Kumbhakar and Lovell, 2000; while a comprehensive review of empirical research is given in Bravo-Ureta et al, 2007). Two main approaches have been developed over time for analysing the technical efficiency of agriculture: (i) the construction of a non-parametric piecewise linear frontier using a linear programming method known as data envelopment analysis (DEA), and (ii) the estimation of a parametric production function using stochastic frontier analysis (SFA). We apply a stochastic frontier analysis to measure efficiency, which is rare in our sample countries (except by Barnes et al, 2010, and Bakucs et al, 2010). In addition, most studies focus on a single country’s agricultural sector (for example, Kelly et al, 2012;
Wilson, 2011); thus the comparative analysis of technical efficiency is rather scarce (see recent exceptions by Barnes et al, 2010, and Zhu and Lansink, 2010, or a multi-country setting of total factor productivity convergence by Galanopoulos et al, 2011). More importantly, readily available farm-level data for research purposes in the EU may help to provide interesting insights for policy makers on farm-level technical efficiency in order to develop more targeted policy, thus improving the overall efficiency of European agriculture.

The aim of this paper is therefore to analyse the stability and mobility patterns of technical efficiency scores for selected EU countries including Belgium, Estonia, France, Germany, Hungary, Italy, the Netherlands and Sweden. The availability of long time-series datasets between 1990 and 2006 (except for the NMS) allows us to concentrate on long-term trends in technical efficiency, especially in the EU15 member states. This study represents the first assessment to provide a comprehensive overview of the long-term trends in technical efficiency, especially in the EU15 variable truncated from below zero, N(0, σ²). However, it is most often considered to be identically and independently distributed drawn from the normal distribution, N(0, σ²). Second, being a parametric approach, we need to specify the underlying functional form of the data generating process, or DGP. There are a number of possible functional form specifications available; however, most studies employ either the Cobb–Douglas (CD) approach:

\[ f(x) = \prod_{k=1}^{K} x_{ik} \]

or the TRANSLOG (TL) specification:

\[ \ln(y) = \sum_{k=1}^{K} \beta_k \ln(x_k) + \frac{1}{2} \sum_{k=1}^{K} \sum_{j=1}^{K} \beta_{kj} \ln(x_k) \ln(x_j) \]

Because the two models are nested, it is possible to test the correct functional form by using 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. Our empirical estimation strategy is simple to general, as follows: start with the more parsimonious functional form (CD) using the available distributional assumptions, then, if convergence cannot be achieved, move to TL specification and estimate across distributional assumptions.

Stability analysis

Efficiency scores as such do not reveal much about the fluctuation of a farm’s relative performance. From a policy point of view, however, an interesting question is whether poorly performing farms are always inefficient, and vice versa: that is, whether farms with higher TE scores are efficient throughout the period. Policy relevance derives from the fact that chronically poorly performing farms may be targeted with specific measures 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 over longer time periods; therefore comparisons were done between consecutive years. We follow the stability analysis methodology outlined by Barnes et al (2010). Yearly farm TE scores were classified by terciles, and then transition matrices linking two consecutive years were constructed to indicate whether the selected farm remained in the same tercile or whether its relative position worsened or, on the contrary, improved.

The degree of mobility in patterns of SFA scores can be summarized using indices of mobility. These formally evaluate the degree of mobility throughout the entire distribution of SFA scores and facilitate direct cross-
Table 1. Descriptive statistics and concentration index of field crop farms (UAA).

<table>
<thead>
<tr>
<th>Country</th>
<th>Utilized agricultural area Mean</th>
<th>Gini coefficient</th>
<th>End period Mean</th>
<th>Gini coefficient</th>
<th>Sample size, total period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Belgium</td>
<td>54.00</td>
<td>0.2975</td>
<td>73.87</td>
<td>0.3159</td>
<td>1,627</td>
</tr>
<tr>
<td>Estonia</td>
<td>230.11</td>
<td>0.4754</td>
<td>240.27</td>
<td>0.4824</td>
<td>505</td>
</tr>
<tr>
<td>France</td>
<td>80.89</td>
<td>0.3436</td>
<td>135.88</td>
<td>0.3323</td>
<td>32,874</td>
</tr>
<tr>
<td>Germany</td>
<td>47.11</td>
<td>0.3501</td>
<td>252.02</td>
<td>0.6358</td>
<td>20,052</td>
</tr>
<tr>
<td>Hungary</td>
<td>255.45</td>
<td>0.6671</td>
<td>240.05</td>
<td>0.6360</td>
<td>2,859</td>
</tr>
<tr>
<td>Italy</td>
<td>19.61</td>
<td>0.5081</td>
<td>50.96</td>
<td>0.6503</td>
<td>69,021</td>
</tr>
<tr>
<td>Netherlands</td>
<td>62.34</td>
<td>0.3220</td>
<td>82.81</td>
<td>0.3684</td>
<td>2,983</td>
</tr>
<tr>
<td>Sweden</td>
<td>83.61</td>
<td>0.2939</td>
<td>120.19</td>
<td>0.4515</td>
<td>2,983</td>
</tr>
</tbody>
</table>

K – tr(P)M1 = \frac{K - \text{tr}(P)}{K - 1} \quad (5)

\text{where } K \text{ is the number of cells, and } P \text{ is the transition probability matrix.}

The second index (M2) after Shorrocks (1978) and Geweke et al (1986) evaluates the determinant (det) of the transition probability matrix.

M2 = 1 - |\text{det}(P)| \quad (6)

In both indices, a higher value indicates greater mobility, with a value of zero indicating perfect immobility. The mobility indices as such can serve only to rank analysed countries’ field crop sectors according to their mobility. In order to explain why certain countries’ technical efficiency scores are more mobile, a second stage regression is performed, regressing mobility scores on a set of explanatory variables. However, this analysis is performed only for the EU15 countries included in this paper, due to the limited time-series data for the new member states (NMS).

Data

The farm-level data used are extracted from the EU Farm Accountancy Data Network (FADN) database. FADN ‘is an instrument for evaluating the income of agricultural holdings and the impacts of the Common Agricultural Policy’ (European Commission, 2013). The FADN database provides bookkeeping data for thousands of commercial farms in the EU. Data are collected by member states and harmonized by the European Commission. For more information on FADN, readers are referred to Barkaszi et al (2009). Due to their relative importance and large number of observations compared with other sectors, field crop farms (TF1) are considered in this paper. The data source is the FADN database from 1990 to the most recent available year (2006) for the EU15 and from 2004 to 2006 for the NMS. Inconsistent data and outliers were removed from the initial datasets through visual and graphical inspection for all variables of interest. Table 1 shows that an obvious concentration process, the increase in average farm size, occurred in all countries analysed during the period. With the exception of Hungary, the sample means of farm size for all countries increased. In some countries, the average sample mean increased dramatically. For example, the farm size measured by ‘utilised agricultural area’ (UAA) of field crop farms in Germany increased fivefold, Italian field crop farm sizes trebled, and Swedish and French field crop farm sizes doubled. The second column for both the start and end periods presents the Gini concentration index. Generally, the concentration index also increases between the start and end periods, but not anywhere near as dramatically as farm size means. The highest sample size means and concentration indices are reported for the NMS, Hungary and Estonia. With the exception of these two countries, however, a higher sample size mean does not necessarily translate into a higher concentration index.

Results

Development of farm efficiency

The technical efficiency (TE) estimates obtained with SFA are plausible when the computed mean technical efficiency scores are largely in line with the results obtained by previous studies. Selected examples in the literature confirm this. For example, Zhu and Oude Lansink (2010) employed the longest time-series data in their research, and focused on several countries also included in this paper, thus serving as a useful benchmark to assess our results. A simple visual inspection of the efficiency estimate figures makes it difficult to determine whether in
the long run the average per country efficiency scores have increased or decreased. We therefore analysed this issue econometrically by regressing the TE scores for each country (for all years pooled) on a single explanatory variable – time trend. Table 2 presents these estimates and their significance levels. Coefficients are significant, small and negative across regressions, suggesting a decreasing average technical efficiency score for each country. The regressions were not performed for NMS since their sample covers only three years of data.

Stability analysis

Following the technique outlined in the methodology, we performed the stability analysis for Belgium, Estonia, France, Germany, Hungary, Italy, the Netherlands and Sweden. Our findings suggest a surprising consistency of results across countries over time. Table 3 presents the mean values of the percentage of farms in consecutive years that remain in the same tercile, along with those increasing or decreasing their respective terciles. As suggested earlier, the results are surprisingly stable, with about 60% of all farms remaining in the same tercile for two consecutive years, whilst about 15–20% of farms decrease or increase their performance, moving down or up a tercile. The results obtained here are consistent with those of Barnes et al (2010) for crop farming in England, Scotland, Wales and Northern Ireland. On average, 15% (Estonia) to 24% (Germany) of field crop farms remained in the top tercile each year, with 13% (Estonia and Hungary) to 17% (Belgium, Germany) in the middle tercile and 17% (Estonia, Hungary) to 22% (France) in the lower tercile (Table 4).

It is probably of more interest to assess 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, while almost the same, on average 10% (France) to 16% (Hungary), fell from the top or middle tercile to the lowest. It is interesting to note that the NMS of Estonia and Hungary registered the highest average percentage of farms that either dramatically increased or decreased 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 means of yearly mobility indexes, M, and Mj (equations 5 and 6) are presented in Table 5. For both indices, a higher value indicates greater mobility, whilst a value close to zero indicates perfect immobility.

Index means are remarkably similar across countries in this research. It is important to note that the Mj index ranks countries in the same way as M, implying consistency of results. Mj ranges from 0.52 to 0.63, whilst M ranges from 0.81 to 0.88, indicating a similar degree of mobility. Mj and M indices are significantly higher for new member states (Estonia and Hungary). Mj reaches 0.97 and 0.99 in Hungary and Estonia, suggesting higher mobility of SFA scores throughout the entire distribution. The lowest mobility scores are recorded for Sweden.

Some determinants of farm mobility

One fundamental research question is whether one can identify factors that influence the mobility indices. An obvious set of explanatory variables would be farm structure and organizational form (for example, family, corporate or cooperative farms); however, these data are available only in national FADN databases. Instead, in this paper we use input ratio variables to capture the land- and/or capital-intensive nature of the crop sector, also available in the EU FADN database. A number of explanatory variables were regressed using different specifications (for example, nominal, log-log) and we present here the panel regression output with the most

<table>
<thead>
<tr>
<th>Field crop</th>
<th>Increase</th>
<th>Remain static</th>
<th>Decrease</th>
</tr>
</thead>
<tbody>
<tr>
<td>Belgium</td>
<td>0.20</td>
<td>0.61</td>
<td>0.19</td>
</tr>
<tr>
<td>Estonia</td>
<td>0.26</td>
<td>0.46</td>
<td>0.28</td>
</tr>
<tr>
<td>France</td>
<td>0.19</td>
<td>0.61</td>
<td>0.20</td>
</tr>
<tr>
<td>Germany</td>
<td>0.20</td>
<td>0.61</td>
<td>0.19</td>
</tr>
<tr>
<td>Hungary</td>
<td>0.26</td>
<td>0.48</td>
<td>0.26</td>
</tr>
<tr>
<td>Italy</td>
<td>0.20</td>
<td>0.59</td>
<td>0.21</td>
</tr>
<tr>
<td>Netherlands</td>
<td>0.20</td>
<td>0.58</td>
<td>0.21</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.18</td>
<td>0.65</td>
<td>0.17</td>
</tr>
</tbody>
</table>

Table 4. Average change in technical efficiencies for field crop farms depending on their tercile movement.
significant results. Since $M_1$ and $M_2$ indices are qualitatively similar, regressing $M_2$ yields more significant results, so we focus on $M_2$ only. Table 6 presents the random effect panel regression results of the mobility index upon farm size (measured in UAA), land per labour, and capital (measured in total assets) per labour input ratios, normalized by their mean. Except for farm size, all explanatory variables and the constant are highly significant. The sign of the coefficients rather than the magnitude is important in this analysis. The regression results emphasize that the higher the land per labour and capital per labour farm input ratios, the less likely it is that the corresponding technical efficiency score changes the position within the distribution during two consecutive years – that is, farms that employ more labour per unit land or capital are more mobile. This finding reinforces mobility results with respect to higher mobility of efficiency scores recorded in the NMS. Capital scarcity, cheaper labour and higher rural unemployment result in a substitution effect in favour of human labour.

Conclusions

The aim of this paper was to present and analyse the farm technical efficiency stability over time, plus the determinants of mobility of the field crop farms for eight countries. The availability of long period data allows us to concentrate on long term trends in technical efficiency. This study is the first to provide a comprehensive overview of the development in farm-level efficiency across these eight countries. Generally, all countries have relatively high levels of mean efficiency ranging from 0.72 to 0.92. A slightly decreasing trend of efficiency may be observed for all countries. Technical efficiency estimates are largely in line with those reported in previous studies. The novelty of the paper is its investigation of how the relative performance of farms fluctuates in terms of technical efficiency over time. We may hypothesize that many poorly performing farms remain inefficient over time, whilst some farmers always perform very efficiently. Theoretically, one could identify farms that are usually at the bottom or top of the efficiency ranking. However, the FADN data have an inherent problem for long time period analysis arising from their rotated panel nature: namely that not all the farms are observed for the whole period. Thus we needed to calculate transition matrices in each consecutive year. The surprisingly robust results reveal that on average 60% of farms maintain their efficiency ranking in two consecutive years, whilst 20% improve and 20% worsen their position. However, these ratios fluctuate slightly from one year to the next. Finally, stability analysis ranked the countries according to their mobility of SFA scores within the distribution. Farms in NMS are more mobile than those in the EU15. This may be due to the unstable economic conditions of farms in these countries where, for example, access to inputs is not always secured or is costly. Further insight into possible determinants of farm technical efficiency mobility is offered by a panel regression of the $M_2$ index upon farm size and the input mix ratio employed. The results highlight the impact of capital scarcity and indeed substitution of capital inputs with labour input upon the volatility in year-to-year farm technical efficiency. Further research could include farm organization and managerial attribute variables amongst explanatory variables to capture the endogenous determinants of technical efficiency scores changing their relative positions in time.

Acknowledgments

This research received funding from the European Community’s Seventh Framework Programme, under grant agreement No 212292, ‘Farm Accountancy Cost Estimation and Policy Analysis of European Agriculture’.

Note

1 This is mainly due to the effects of the German reunification process, through the inclusion of the large-scale former GDR state-owned agricultural holdings in the sample.

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