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# Estimating technical efficiency under technological heterogeneity in Hungarian crop sector

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## Abstract

Technological heterogeneity is an important issue in studies of agricultural production. We assume that this is much more serious in transition countries, since the agricultural sector in these countries is characterized by the presence of even more different technologies and structures. Previous studies address the issue of production heterogeneity in developed countries; however, there is a clear lack in the literature concerning the effect of different technologies in transition countries. There are two common approaches to estimate different technologies: the most common one is to split the sample into groups based on some a priori information; an alternative method is the latent class models. In the present paper both approaches are used to identify different technologies and to estimate technical efficiency. It seems to be that the LCM model identified better technological differences and separated better the effect of heterogeneity and technical efficiency.

**Keywords** Technical efficiency; Heterogeneity; Latent class model; Hungarian agriculture

**JEL code** Q12

## **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).

There are a lot of methodological issues in efficiency literature. One important problem is the technological heterogeneity which has obvious relevance in the agriculture (Corral et al., 2009). This problem might be more serious in transition countries, since the agricultural sector in these countries is usually characterized by a dual structure implying more different technologies comparing to the Western European countries. There are two common approaches to estimate different technologies within a sample of farms. The most common methodology is to use two-stage procedure. In the first step, the sample is splitted into several subgroups based on some a priori information about farms and then in the second stage different functions are estimated for each group. Alternative method is the latent class model which assumes that there are a finite number of classes underlying the data (Corral et al., 2009; Alvarez-Corral, 2010).

In this paper we use both approaches. First, we split our sample into individual and corporate farms; with the result that previous studies found significant differences between technical efficiency scores of individual and corporate farms. However, these studies assumed that the production technology is common to all producers. Hungarian agriculture has a typical dual structure; half of the utilised agricultural area is managed by individual farms, whilst the rest is cultivated by companies. The average farm size for individual farms is much lower compared to corporate farms, consequently they might use different technologies. According to Orea and Kumbhakar (2003): in such a case estimating a common frontier function may not be appropriate

in the sense that the estimated technology is not likely to represent the 'true' technology. Our aim is to investigate how the estimation of different frontiers influences technological parameters and efficiency scores?

Nevertheless, as Corral et al. (2009) stated: using one single a priori characteristic is might not a complete proxy for the characterisation of a technology, because it may not exhaust all technological differences that exist between farms. For this reason at the second step of our analysis, we are going to use an LCM model and to compare the results of this model with the previous method. We focus on following questions:

- (1) Do individual and corporate farms use different technologies in Hungarian crop sector?
- (2) Is it reasonable and does it yield better results to estimate different production frontiers for the groups mentioned before?
- (3) How do the results of an LCM model differ from (i) a model which assumes that the technology is common to all farms and (ii) from a model which uses a priori information?
- (4) How do the results of technical efficiency scores differ using the approaches stated above?

The paper is organised as follows. Section 2: discuss previous efficiency studies concerning Hungarian agriculture, Section 3: reports the method; Section 4: outlines the data and empirical model used. Finally the paper summarizes the main findings.

## **Previous studies about efficiency in Hungarian agriculture**

Recent papers employ both DEA and SFA approaches for the analysis of technical efficiency of Hungarian agriculture. Latruffe et al (2011) investigate the differences in technical efficiency and productivity change, and the technology gaps, between French and Hungarian farms in the dairy and cereal, oilseed and protein crops (COP) sectors during the period 2001–2007 using DEA approach under each country's respective frontier and under a metafrontier. Results reveal that French COP farms were on average more efficient under their own technology than Hungarian farms under theirs, but there was no difference between the two countries for dairy farms. However, metatechnology ratios calculated with the construction of the metafrontier indicate that Hungarian technology was the more productive in both the dairy and the COP sectors, but more noticeably in COP production.

Latruffe et al. (2010) examine the relationship between the technical efficiency of farms specialised in pig production and the environmental pressures that they are currently facing or may face in the future in Hungary employing DEA approach. Pig farms' technical efficiency was calculated with pig activity data in 2001, including the quantity of nitrogen produced by livestock as a strongly disposable undesirable output. Results imply that neighbourhood pressures regarding environmental pollution increased farms' technical efficiency, while congestion problems due to a large regional nitrogen production reduced the efficiency.

Bakucs et al. (2010) used stochastic frontier analysis to evaluate technical efficiency of Hungarian farms before and after accession to the European Union (EU), and to investigate the efficiency determinants. The results show that EU membership has reversed the pre-accession process of efficiency decrease. But the other side of the coin is that access to higher post-accession subsidies contributes to lower efficiency of Hungarian farmers. The other remarkable finding is a seeming scarcity of labour on farms, which constrains their production and efficiency. The Hungarian government may therefore have to design specific national policies if its aim is to promote a farming system that uses labour and at the same time is competitive

Bakucs et al. (2012) investigate the technical efficiency of Hungarian dairy farms between 2001 and 2008 using stochastic frontier analysis. The paper focuses on three specific issues: the impact of the European Union accession, the role of farm organisation and the effect of farm size. Results highlight the role of farm classification in explaining the performance of dairy farms. Main finding is that individual farms are not equivalent to family farms as is usually assumed in previous research. The average size of individual farms is considerably bigger than that of family farms. Estimations confirm that mean performance of individual and family farms is weaker than of the corporate farm organisation including companies, cooperatives, intermediate and non-family farms irrespective of the methods, product group and country. The simple mean comparison estimation shows that there are significant differences in farm performance among farms in terms of legal form or farm organisation. However, panel regression just partly confirms these results. Although estimations indicate that the impact of family and individual farms on farm performance is rather negative, some other farm type coefficients remain not significant.

In sum, recent studies identify some potential factors affecting technical efficiency including farm size, farm organisation and policy measurements. However, all of these studies on technical efficiency of Hungarian agriculture (implicitly) assumed that the technology is the same for all farms. To the best of our knowledge there has been no study aiming to analyse the effect of unobserved technological differences using a latent class model in Hungarian crop sector. If unobserved technological differences are not taken into account, technical efficiency scores are might be underestimated. The aim of the paper is to contribute to this issue.

## Methodology

The two most common approaches to estimate technical efficiency are the Data Envelopment Analysis (DEA) and the Stochastic Frontier Analysis (SFA). DEA is a more flexible approach in a sense that it doesn't require the assumption of a special functional form, transforming inputs into outputs; however, it reacts very sensitively to outliers and inconsistencies in the data. In contrast, using SFA one has to make assumptions regarding the form of the production function and the distribution of inefficiencies.

In this paper we use the stochastic frontier approach. The stochastic production frontier was originally proposed by Aigner, Lovell and Shmidt (1977) and Meeusen and van den Broeck (1977), independently from each other.

A stochastic frontier may be written as:

$$\ln y_i = \alpha + \beta'x_i + v_i - u_i,$$

where  $y$  represents the output of each farm,  $x$  is a vector of inputs,  $v_i$  captures statistical noise, and  $u_i$  represents the inefficiency.

In order to fulfil our aims we estimate two differently specified stochastic frontier models. First, we estimate an SFA model for individual and corporate farms separately then we use a stochastic frontier latent class model.

Following to Alvarez and Corral (2010) a latent class Model can be written as follows:

$$y_{it} = f(x_{it})|j * \exp(v_{it}|j - u_{it}|j),$$

where  $i$  represents farm,  $t$  denotes time and  $j$  indicates the different classes. The vertical bar means that there is a different model for each class  $j$ .

For the half-normal model, the likelihood function (LF) for each farm  $i$  at time  $t$  for group  $j$  can be written as (Kumbhakar and Lovell, 2000):

$$LF_{ijt} = f(y_{it}|x_{it}, \beta_j, \sigma_j, \lambda_j) = \frac{\Phi(-\lambda_j * \varepsilon_{itj} / \sigma_j)}{\Phi(0)} * \frac{1}{\sigma_j} * \phi\left(\frac{\varepsilon_{itj}}{\sigma_j}\right),$$

where  $\varepsilon_{itj} = y_{it} - \beta_j' x_{it}$ ,  $\sigma_j = [\sigma_{uj}^2 + \sigma_{vj}^2]^{1/2}$ ,  $\lambda_j = \sigma_{uj} / \sigma_{vj}$ , and  $\phi$  and  $\Phi$  denote the standard normal density and cumulative distribution function, respectively.

The contribution of farm  $i$  to the conditional (on class  $j$ ) likelihood is (Greene, 2005):

$$LF_{ij} = \prod_{t=1}^T LF_{ijt}.$$

The LF for each farm is obtained as a weighted average of its LF for each group  $j$ , using the prior probabilities of class  $j$  membership as weights (Alvarez and Corral, 2010):

$$LF_i = \sum_{j=1}^J P_{ij} LF_{ij}.$$

There are many ways to parameterise  $P_{ij}$  (Green, 2005); a convenient way is the multinomial logit (Greene, 2005; Alvarez and Corral (2010)):

$$P_{ij} = \frac{\exp(\delta_j q_i)}{\sum_{j=1}^J \exp(\delta_j q_i)},$$

where  $q_i$  is a vector of separating variables which are individual (farm) characteristics that sharpen the prior probabilities, and  $\delta_j$  is a vector of parameters to be estimated.

The equation of the overall log LF is the sum of the individual log LFs (Greene, 2005; Alvarez and Corral (2010)):

$$\log LF = \sum_{i=1}^N \log LF_i.$$

## Data & Empirical Model

For the empirical analysis we used *an unbalanced panel data set from a Hungarian Farm Accountancy Data Network (FADN)* for the period 2001 to 2009; the total numbers of observations was 9612. The data was provided by the Hungarian Agricultural Research Institute.

These survey data are aggregated in 2 different ways. One way is the so-called national database, which is suited to Hungarian bookkeeping laws; the second is converted into the form of standard tables (Keszthelyi, 2007). These data are harmonised according to the bookkeeping principles of the European Union. For this analysis, we use the database mentioned secondly of farms specialized in field cropping (TF 13, 14, 60), complemented with Hungarian national FADN data. In addition to the EU FADN data, the Hungarian national data contains important information about farm manager characteristics such as age and education, about farm structural characteristics such as soil quality and farm legal form.

We use one output (Y) (total agricultural production) and 4 inputs (labour ( $x_1$ ), land ( $x_2$ ), capital ( $x_3$ ) and intermediate consumption ( $x_4$ )). Additionally, time variables (t), (tt) were added to the production function to capture the effect of technological change; time trend is interacted with the input variables to allow for non-neutral technical change. All variables expressed in current value were deflated to the year 2005, using the appropriate deflators. Specifically, we used the agricultural output index to deflate the agricultural production. The intermediate consumption and the capital stock were deflated by the price index of purchased goods and services and by the investment price index, respectively.

Some descriptive statistics about the variables used are presented in Table 1.

**Table 1: Descriptive Statistics**

	<b>Mean</b>	<b>Std.Dev.</b>	<b>Minimum</b>	<b>Maximum</b>	<b>N</b>
<b>Total output (euro)</b>	149,916	465,849	235.74	17,786,600	9,612
<b>Labour input (AWU)</b>	4.66	14.06	0.01	455.11	9,612
<b>Land (ha)</b>	246.13	511.61	0.60	9,994.85	9,612
<b>Fixed assests (euro)</b>	151,919	362,326	55.49	17,224,500	9,612
<b>Interm. consum. (euro)</b>	86,813.3	285,677	763.84	2,974,900	9,612

Source: Own calculation



The empirical specification of the production frontier is translog. The input variables were divided by their geometric means so the estimated first order coefficients can be interpreted as the production elasticity evaluated at the sample geometric means.

The specification of the production frontier to be estimated for individual and corporate farms can be written as:

$$\ln y_{it} = \beta_0 + \sum_{k=1}^K \beta_k \ln x_{kit} + \frac{1}{2} \sum_{k=1}^K \sum_{l=1}^K \beta_{kl} \ln x_{kit} \ln x_{lit} + \beta_{kt} \ln x_{kit} * t + v_{it} - u_{it}$$

Whereas the equation for the LCM model is as follows:

$$\ln y_{it} = \beta_0|_j + \sum_{k=1}^K \beta_k|_j \ln x_{kit} + \frac{1}{2} \sum_{k=1}^K \sum_{l=1}^K \beta_{kl}|_j \ln x_{kit} \ln x_{lit} + \beta_{kt}|_j \ln x_{kit} * t + v_{it}|_j - u_{it}|_j$$

All models were estimated by using Limdep.

## Results

In this section we first present and discuss the parameter estimates of the different production frontiers estimated for all farms (ALL\_F) for the groups identified using a priori information (Individual farms (IF) and Corporate farms (CF) and the groups identified by the LCM model (C1, C2). Secondly we compare the differences of some representative variables among the groups obtained. The third step of this section concerns the investigation of the development of technical efficiency scores. Table 2 reports the parameter estimates.

**Table 2: Parameter Estimates**

	All_F	IF	CF	C1	C2
<b>Constant</b>	.32085***	.27919***	.39055***	.36340***	.21782***
<b>T</b>	.01802***	.01531***	.02520***	.02060***	.01776***
<b>TT</b>	-.02076***	-.02324***	-.00913**	-.01348***	-.02439***
<b>Labour</b>	.17140***	.14046***	.29531***	.21125***	.10669***
<b>Land</b>	.28466***	.27236***	.26742***	.30767***	.26459***
<b>Capital</b>	.11543***	.11895***	.13326***	.13977***	.09179***
<b>Int. Cons</b>	.46672***	.50480***	.37723***	.38336***	.56693***
<b>Lab*land</b>	-.06864***	-.09276***	-.08492***	-.09191***	-.05158***
<b>Lab*Cap</b>	.00907*	.02116***	.02297*	.03421***	-0.00063
<b>Lab*IC</b>	-.03208***	-0.0134	-.06258***	-.08285***	-.02346*
<b>Land*Cap</b>	-.03971***	-.05657***	0.01475	-.04956***	-.04141***
<b>Land*IC</b>	-.06446***	-.03826***	0.01278	-.15163***	-.06743***
<b>Cap*IC</b>	-0.00777	-0.01545	-.06210***	-.03491**	0.00178
<b>Lab*Lab</b>	.13515***	.12663***	.08960***	.18314***	.10440***

<b>Land*Land</b>	.16232***	.17726***	0.03481	.27784***	.15278***
<b>Cap*Cap</b>	.04195***	.05746***	.02384**	.06283***	.02724***
<b>IC*IC</b>	.09281***	.07832***	.14404***	.25462***	.09674***
<b>T*lab</b>	-0.00259	-0.00298	-.01258**	0.00549	-.00989***
<b>T*land</b>	0.00372	0.00258	-0.00295	.01338**	0.00599
<b>T*Cap</b>	-.00342**	-.00520**	0.00402	-.00851***	0.00139
<b>T*IC</b>	.00480**	.00735**	0.00689	-.00961*	0.00387
<b>Sigma (U)</b>	.44085***	.42046***	.50916***	0.244715	0.502023
<b>Lambda</b>	1.32351***	1.24295***	1.40698***	.83975***	2.73396***

Source: Own estimation

Most of the coefficients are positive and significant in all models. There are big differences between the parameter estimates in the different models, which suggest that might exist different technologies within the Hungarian crop producing farms so it is important to handle the effect of heterogeneity to receive unbiased technical efficiency scores.

The  $\lambda$  parameters estimated demonstrate that the deviation from the theoretic production frontier is mostly due to the inefficiency effect (except group 1 identified by LCM model), the  $\lambda$  s are greater than 1, which confirms that inefficiency variation has a significantly larger impact on output variation than the pure random component.

The results illustrate that the biggest difference can be seen regarding technological parameters in the case of labour's elasticity. Every model yields similar results for the elasticity of land and capital. Moreover, in every case intermediate input is the most influential in production in terms of elasticity. All of the models reveal that technological progress occurred over the period analysed, ( $\alpha_t > 0$ ); however, the growth rate was decreasing  $\alpha_{tt} < 0$ .

The sum of the production elasticity is above one in every group (IF:1.04; CF:1.06; C1:1.04; C2:1.03) suggesting increasing return to scale at the sample mean.

To sum up the discussion of parameter estimates, we can state that technological parameters between the groups received using a priori information and the groups received by the LCM model differ markedly from each other. In order to get more insight into the characteristic of these groups, Table 3 represents some descriptive variables about them.

**Table 3: Characteristics of different groups (sample means)**

	<b>IF</b>	<b>CF</b>	<b>C1</b>	<b>C2</b>
<b>Total Output (1000 eur)</b>	54.80	575.43	174.66	134.43
<b>Labour (AWU)</b>	1.55	18.59	4.51	4.75
<b>LAND (ha)</b>	109.34	858.14	237.85	251.32
<b>Fixed Assets (1000 eur)</b>	99.06	388.38	154.96	150.02
<b>Interm. Consumpt. (1000 eur)</b>	30.79	337.45	90.68	84.40
<b>Technical efficiency</b>	0.73	0.74	0.91	0.80
<b>Number of observations</b>	7856	1756	3700	5912

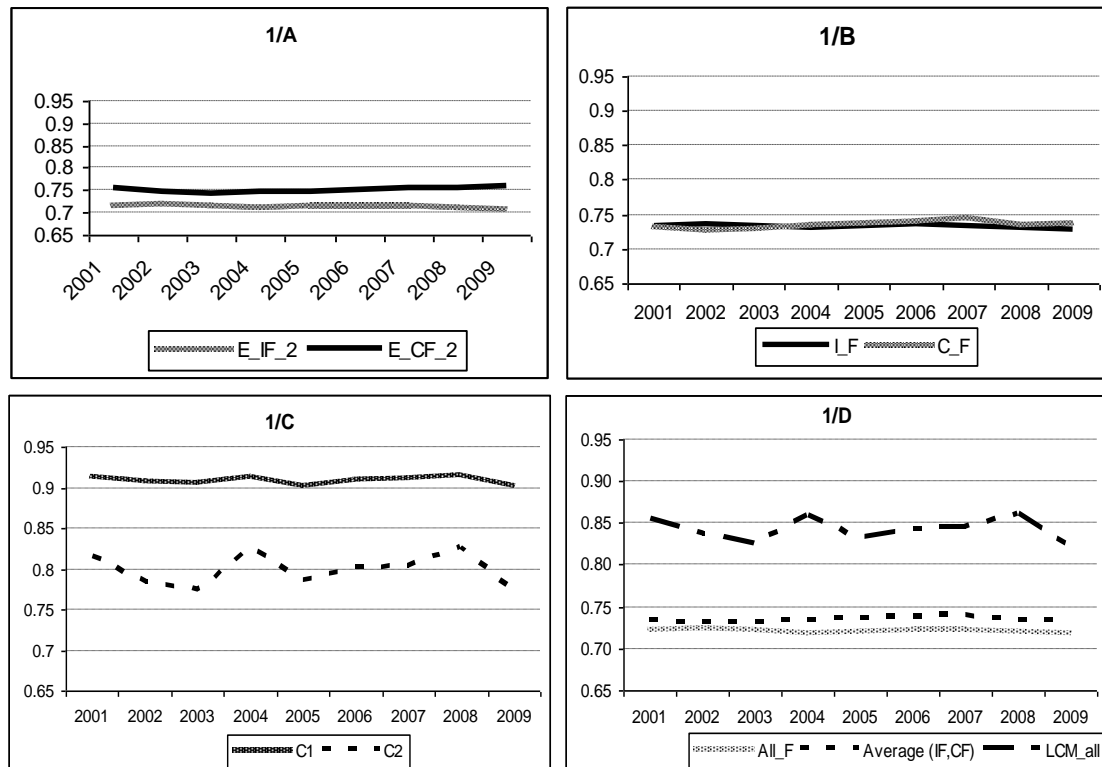
Source: Own calculation

Table 3 demonstrates that there are huge differences between individual and corporate farms in Hungarian cropping sector regarding the output and input variables; total output and inputs is a great deal bigger in corporate farms. However, between the estimated average technical efficiency scores reveal only moderate difference. In addition, the two groups obtained by the LCM model show totally different characteristics compared to individual and corporate farms, which might be a sign that using one single characteristic (namely in our paper: farm's legal form) may not be an appropriate proxy for the characterisation of the technology. The groups found by the LCM model are similar to each other in terms of output and input scale, but between the estimated TE scores reveal large differences. For this reason at the next step of our analysis we investigated TE in more detail (Graph 1).

Graph 1/A shows the development of technical efficiency year by year in individual and corporate farms in the case when a common production frontier was assumed, whereas Graph 1/B illustrates the results when a separated production frontier was estimated for IF and CF. It can be clearly seen that the difference between individual and corporate farms regarding TE is becoming smaller in the second case.

Graph 1/C shows the development of TE by groups obtained in the LCM model. We can state that the difference is across these groups is considerably greater. This suggest (again) that there are latent technological differences among farms which is larger than technological differences between individual and corporate farms, consequently using an LCM model might be a better method to estimate TE in Hungarian crop sector. The TE scores of these groups imply that there might be a group within Hungarian cropping sector which is constantly more

efficient than the other, and not only more efficient but the evolution of technical efficiency over time is also more stable in the case of this group.



**Graph 1: The development of technical efficiency scores**

Source: Own calculation

Graph 1/D shows the development of average TE scores received by the different models. As it was expected average TE is the lowest when a common frontier was estimated (All\_F), the estimation of a separated frontier for IF and CF yields a bit higher average TE score, yet the difference is not significant. The LCM model revealed substantially higher average technical efficiency. Although, both of the last two approaches allow farms to measure to its own frontier, it seems to be that the LCM model separate better technological heterogeneity from technical efficiency. The difference between the results received by the estimation of a common frontier and the LCM model is more than 10%, which suggests that dealing with the effect of heterogeneity is important in Hungarian crop sector.

## Conclusion

In this paper we apply two approaches to identify different technologies in Hungarian crop sector. First, we split our sample into individual and corporate farms using a priori information and estimated different production frontiers for these groups. Second, we employ

an LCM model. Our aim was to compare the results of these two methods with each other and with a method which use one common production frontier for all farms.

The results identify technological differences between individual and corporate farms, and between groups found by the LCM. Different models yielded different technical efficiency scores. Average TE was the highest in the case of the LCM – according to theoretical expectations, and was the lowest in the case of one common frontier. These suggest that technological heterogeneity is a relevant issue in Hungarian crop sector and it is important to handle this effect to get more appropriate TE scores. At this stage of our research the LCM Model seems to be adequate for this purpose.

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