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ANALYSING THE DETERMINANTS OF LITHUANIAN FAMILY FARM PERFORMANCE: A DOUBLE BOOTSTRAP INFERENCE

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Abstract. The efficiency analysis often involves the second stage analysis which enables to identify certain drivers of efficiency. However, suchlike inference is problematic due to the nature of the frontier measures. This paper employed the double bootstrap procedure (Simar, Wilson, 2007) to analyse the determinants of the efficiency on Lithuanian family farms. The double bootstrap method was employed to estimate the efficiency scores by the means of the data envelopment analysis and to regress them on the explanatory variables. The analysis was based on the farm-level data from the Farm Accountancy Data Network. Specifically, the second stage analysis included the variables of time, farm size, asset input, specialisation, and subsidy rate. The results did indicate that the period of 2004–2009 was generally associated with an increase in efficiency. Furthermore, larger farms appeared to be more efficient. Even though, livestock farming has been declining in Lithuania, the findings of the paper implied that the latter type of farming exhibited higher efficiency in general.

Key words: family farms, efficiency, Lithuania, frontier, double bootstrap.

JEL code: C24, C44, C61, Q12.

Introduction

Efficiency analysis is often followed by the second-stage analysis to estimate the impact of certain efficiency determinants. Suchlike inference might be useful for understanding the underlying trends of efficiency and, thus, reasonable policy making. The second-stage analysis can be based on various techniques (Hoff, 2007; Bogetoft, Otto, 2011).

Initially, the ordinary least squares (OLS) regression was considered as a primal tool for post-efficiency analysis. The latter method is attractive in that its coefficients are easy to interpret. However, it is obvious that efficiency scores are bounded to certain intervals which depend on both the type and the orientation of the distance functions. Consequently, the censored regression (tobit model) emerged as a remedy. Later on, however, Simar and Wilson (2007) argued that the censored regression models suffered from certain drawbacks. First, the underlying data generating process does not generate censored variables. Indeed, it is the finite sampling that causes efficiency estimates concentrated around unity. Second, censored model's errors are serially correlated. Therefore, they suggested using truncated regression alongside bootstrapping (Efron, Tibshirani, 1993) in order to avoid the serial correlation. The proposed methodology is, thus, referred to as the double bootstrapping.

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The double bootstrap procedure was implemented in analyses dedicated for various economic sectors (Assaf, Agbola, 2011; Alexander et al., 2010; Afonso, Aubyn, 2006). Though, there are few examples of application of the double bootstrap methodology for the studies of agricultural efficiency. Latruffe et al. (2008) analysed the performance of the Czech farms, both private and corporate ones. Balcombe et al. (2008) employed the double bootstrap methodology to identify the determinants of efficiency in Bangladesh rice farming. Olson and Vu (2009) utilised single and double bootstrap procedures to analyse farm household efficiency.

The Lithuanian agricultural sector was analysed by the means of the bootstrapped Data Envelopment Analysis (DEA) by Balezentis and Krisciukaitiene (2012); however, no second stage analysis was implemented. Therefore, there is a need for further analysis of the drivers of efficiency on the Lithuanian family farms. Indeed, suchlike analyses might help improve the agricultural policy. This paper, thus, aims at identifying the factors of (in)efficiency amongst the Lithuanian family farms. The research object is Lithuanian family farms reporting to the Farm Accountancy Data Network.

This paper employed the double bootstrap methodology (Simar, Wilson, 2007) to examine the factors of efficiency on Lithuanian family farms. The sample of 200 family farms over 6 years (1200 observation in total) was used to establish a production frontier and conduct the second stage regression. The FEAR package was applied for the analysis (Wilson, 2008).

Preliminaries for the double bootstrap

This section presents the methodology of the double bootstrap (Simar, Wilson, 2007). First, the technology set and the DEA estimator are discussed. Second, the truncated regression is presented. Third, the unifying algorithm of the double bootstrap is presented.

Productive technology and efficiency measures. The activity analysis defines the production technology with respect to inputs represented by a $(1\times p)$ vector $x\in\Re_+^p$, and outputs represented by a $(1\times q)$ vector $y\in\Re_+^q$. Furthermore, a $(1\times r)$ vector $z\in\Re_+^r$ comprises the environmental variables. The technology set, *T*, consists of all feasible production plans:

$$T=\left\{(x,y)\in\Re_+^{p+q}\mid x \text{ can produce } y\right\}. \tag{1}$$

Then, the output-oriented Farrell (1957) measure of efficiency for an arbitrary point, (x_0,y_0), is defined as:

$$\delta_0=\delta\left(x_0,y_0\mid T\right)\equiv\sup\left\{\delta\mid\left(x_0,\delta_0 y_0\right)\in T,\delta>0\right\}. \tag{2}$$

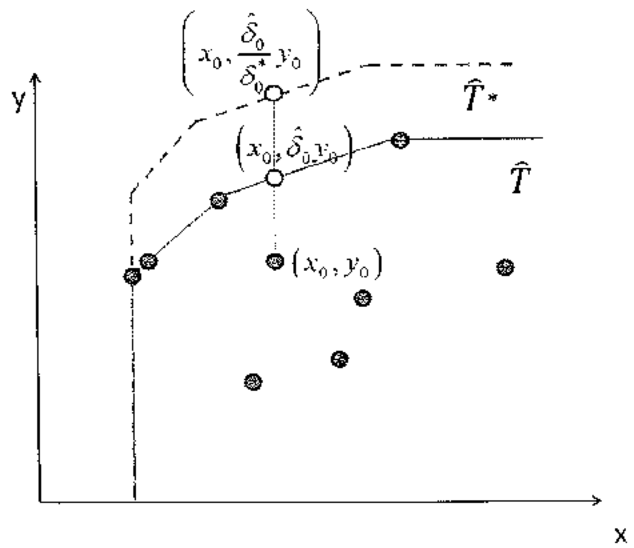
Indeed, the underlying technology set usually remains unknown and the analysis is based on its approximation determined by a set of observations, $S_K=\left\{\left(x_k,y_k,z_k\right)\right\}_{k=1}^K$, where k is the index of the decision making units (DMUs). Under assumptions of free disposability and convexity, T is given by

$$\hat{T}=\left\{(x,y)\in\Re_+^{p+q}\left|\begin{array}{l}\sum_{k=1}^K\lambda_k x_{i,k}\le x_i,\sum_{k=1}^K\lambda_k y_{j,k}\ge y,\sum_{k=1}^K\lambda_k=1,\\ i=1,2,\dots,p,j=1,2,\dots,q,k=1,2,\dots,K\end{array}\right.\right\}. \tag{3}$$

Therefore, the Farrell's output-oriented measure of efficiency can be estimated by employing the following linear program:

$$\hat{\delta}_0 = \max\left\{\delta > 0 \left| \begin{array}{l} \sum_{k=1}^{K} \lambda_k x_{i,k} \le x_{i,0}, \sum_{k=1}^{K} \lambda_k y_{j,k} \ge \delta y_{j,0}, \sum_{k=1}^{K} \lambda_k = 1, \\ i = 1,2,...,p, j = 1,2,...,q, k = 1,2,...,K \end{array} \right.\right\}, \tag{4}$$

where δ_0 becomes greater than unity as an arbitrary observation, (x_0, y_0), is located further from the efficiency frontier. Fig. 1 presents a graphical interpretation of the model given by Eq. 4. The solid line there denotes an approximation, $\hat{T}$, of the true production possibility set, T. Note that the true production possibility set remains unknown and, thus, is approximated by the bootstrap frontiers denoted by the dashed line in Figure 1. An arbitrary observation, (x_0, y_0), is projected onto the efficiency frontier by keeping the output-mix fixed at the point $(x_0, \delta_0 y_0)$. This is a radial movement in an output space from the point of origin through an observation towards the frontier.



Source: author' s construction

Fig. 1. An output-oriented DEA model

The obtained efficiency measures can be further analysed in the second stage analysis. Obviously, the two directions emerge: (i) the true production frontier needs to be estimated; and (ii) the efficiency scores need to be related with the environmental variables. The bootstrap procedure tackles the former issue; whereas, the truncated regression is employed for the latter one.

Truncated regression. The regression model can be given as

$$\vartheta_k = z_k \beta + \varepsilon_k, \tag{5}$$

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where β is a $(r \times 1)$ vector of parameters associated with respective environmental variables, $\varepsilon_k \sim N(0, \sigma_\varepsilon^2)$ is independently distributed for all $k = 1, 2, \ldots, K$. The variable ϑ_k is said to be truncated at c_k in case one can observe $\theta_k = \vartheta_k$ for all $\vartheta_k \geq c_k$, albeit observe nothing otherwise (Simar, Wilson, 2007).

The truncated regression can be estimated via the maximal likelihood method. Specifically, if ϑ_k are assumed to be distributed under the normal distribution with left-truncation at c_k, the vector of parameters, β, for Eq. 5 can be estimated by maximising the following likelihood function:

$$L = \prod_{k=1}^{K} \frac{1}{\sigma_\varepsilon} \phi\left(\frac{\theta_k - z_k\beta}{\sigma_\varepsilon}\right)\left[1 - \Phi\left(\frac{c_k - z_k\beta}{\sigma_\varepsilon}\right)\right]^{-1}, \tag{6}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the standard normal density and distribution functions, respectively.

In the framework of the output-oriented efficiency analysis, one has a left-truncation at unity. Therefore, the determinants of efficiency are analysed by employing the following model:

$$\hat{\delta}_k = z_k\beta + \varepsilon_k \geq 1, \tag{7}$$

where $\hat{\delta}_k$ is an estimate of δ_k (cf. Eq. 4).

An algorithm for the double bootstrap. Simar and Wilson (2007) proposed the two methods for double bootstrapping. In this paper, the author will present and employ Algorithm No 2. The algorithm involves the two main stages: 1) the true production frontier is estimated by the means of output correction; and 2) the truncated regression is estimated to relate the efficiency measures with the explanatory variables, z_k. Indeed, the point $\left(x_0, \hat{\delta}_0 y_0 / \delta_0^*\right)$ in Figure 1 depicts the bootstrap bundle of inputs and the corrected (stimulated) outputs. Note that thanks to the nature of the DEA, the underlying frontier can be shifted upwards with respect to the originally observed one but never inwards.

Algorithm #2 in Simar and Wilson (2007) proceeds as follows:

1. Estimate the Farrell efficiency scores, $\hat{\delta}_k = \delta\left(x_k, y_k \mid \hat{T}\right), \forall k = 1, 2, ..., K$, with respect to the observed data set, S_K, by employing Eq. 4.
2. Use the truncated regression of $\hat{\delta}_k > 1$ on z_k (Eq. 7) to obtain the estimates $\hat{\beta}$ and $\hat{\sigma}_\varepsilon$ of β and σ_ε, respectively.
3. Loop over steps 3.1–3.4 L_1 times to obtain K sets of bootstrap estimates, $B_k = \left\{\hat{\delta}_{kb}^*\right\}_{b=1}^{L_1}$:

3.1. For each $k=1,2,\ldots,K$, draw ε_k from the distribution $N\left(0,\hat{\sigma}_\varepsilon^2\right)$ with left-truncation[1] at $\left(1-z_k\hat{\beta}\right)$.

3.2. For each $k=1,2,\ldots,K$, compute $\delta_k^* = z_k\hat{\beta}+\varepsilon_k$, where ε_k has been drawn in Step 3.1.

3.3. Set $x_k^* = x_k$ and $y_k^* = \hat{\delta}_k y_k / \delta_k^*$ for all $k=1,2,\ldots,K$.

3.4. Estimate the bootstrap efficiency scores, $\hat{\delta}_k^* = \delta\left(x_k, y_k \mid \hat{T}^*\right), \forall k=1,2,...,K$, with $\hat{T}^*$ being defined by replacing the original input-output vectors in Eq. 3 with the corrected ones obtained in Step 3.3, i.e. Eq. 4 is modified by changing the left hand sides of inequalities in restrictions[2].

4. For each $k=1,2,\ldots,K$, compute the bias-corrected estimates of the efficiency scores, $\hat{\hat{\delta}}_k$, by employing the bootstrap replications, B_k, along with the original estimates, $\hat{\delta}_k$:
$$\hat{\hat{\delta}}_k = \hat{\delta}_k - bias\left(\hat{\delta}_k\right) = \hat{\delta}_k - \left(\frac{1}{L_1}\sum_{b=1}^{L_1}\hat{\delta}_{kb}^* - \hat{\delta}_k\right).$$

5. The bias-corrected efficiency scores, $\hat{\hat{\delta}}_k$, are regressed on z_k (cf. Eq. 7) to obtain the estimates of parameters $\left(\hat{\hat{\beta}}, \hat{\hat{\sigma}}_\varepsilon\right)$.

6. Loop over Steps 6.1-6.3 L_2 times to obtain a set of bootstrap estimates $C=\left\{\left(\hat{\hat{\beta}}^*, \hat{\hat{\sigma}}_\varepsilon^*\right)_b\right\}_{b=1}^{L_2}$:

6.1. For each $k=1,2,\ldots,K$, draw ε_k from the distribution $N\left(0,\hat{\hat{\sigma}}_\varepsilon^2\right)$ with left-truncation at $\left(1-z_k\hat{\hat{\beta}}\right)$.

6.2. For each $k=1,2,\ldots,K$, compute $\delta_k^{**} = z_k\hat{\hat{\beta}}+\varepsilon_k$, where ε_k has been drawn in Step 6.1.

6.3. Regress δ_k^{**} on z_k (cf. Eq. 7) to obtain the maximum likelihood estimates $\left(\hat{\hat{\beta}}^*, \hat{\hat{\sigma}}_\varepsilon^*\right)$.

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[1] The i.i.d. draws from $N\left(0,\sigma^2\right)$ with left-truncation at c can be facilitated by considering the standard normal distribution function, $\Phi(\cdot)$, and its inverse, $\Phi^{-1}(\cdot)$ as well as the randomly drawn variable, v, where $v \sim Uniform(0,1)$. After drawing v and setting $v' = \Phi(c') + \left(1-\Phi(c')\right)v$ with $c' = c/\sigma$, the desired left-truncated normal deviate can be given as $u = \sigma\Phi^{-1}(v')$.

[2] The DEA estimator then becomes $\hat{\delta}_0 = \max\left\{\delta > 0 \middle| \begin{array}{l} \sum_{k=1}^{K}\lambda_k x_{i,k}^* \le x_{i,0}, \sum_{k=1}^{K}\lambda_k y_{j,k}^* \ge \delta y_{j,0}, \sum_{k=1}^{K}\lambda_k = 1, \\ i=1,2,...,p, j=1,2,...,q, k=1,2,...,K \end{array}\right\}$.

Use the bootstrap values, C, and the original estimates, $\left(\hat{\hat{\beta}},\hat{\hat{\sigma}}_\varepsilon\right)$, to construct the confidence intervals for each element of β and σ_ε.

The confidence intervals for β_l, the l-th element of β, could be established if the distribution of $\left(\hat{\hat{\beta}}_l-\beta\right)$ were known. Indeed, it would be enough to find the values a_α and b_α such that $\Pr\left(-b_\alpha \le \left(\hat{\hat{\beta}}_l-\beta_l\right) \le -a_\alpha\right)=1-\alpha$. Given the distribution $\left(\hat{\hat{\beta}}_l-\beta\right)$ is unknown, the confidence intervals are constructed on a basis of the bootstrap values $\hat{\hat{\beta}}^*$: $\Pr\left(-b_\alpha^* \le \left(\hat{\hat{\beta}}_l^*-\hat{\hat{\beta}}_l\right) \le -a_\alpha^*\right)\approx 1-\alpha$, where $0\le\alpha\le 1$ is a confidence level. The latter method is referred to as the percentile method. Furthermore, Efron and Tibshirani (1993, p. 184f) presented the bias-corrected accelerated (BC_a) method for estimation of confidence intervals.

Research results

The technical efficiency (TE) was assessed in terms of the input and output indicators commonly employed for agricultural efficiency and productivity analyses. More specifically, the utiliSed agricultural area (UAA) in hectares was chosen as land input variable, annual work units (AWU) – as labour input variable, intermediate consumption in Litas, and total assets in Litas as a capital factor. The monetary variables were deflated by respective real price indices. On the contrary, the three output indicators representing crop, livestock, and other outputs in Litas were deflated by respective real indices and aggregated into a single output indicator.

The data for 200 farms selected from the FADN sample cover the period of 2004–2009. Therefore, a balanced panel of 1200 observations is employed for the analysis. The analysed sample covers relatively large farms (mean UAA – 244 ha). As for labour force, the average was 3.6 AWU. The data were analysed in a cross–section way.

The following variables were chosen for the second stage analysis: the time trend (*Time*) was used to assess whether a general increase in efficiency scores was observed throughout the research period. The UAA in hectares (*UAA*) was used as a proxy for farm size. A ratio of assets to labour force in AWU (*Assets/AWU*) was used to capture the degree of sufficiency of the capital. The share of the crop output in the total output (*Crop*) was employed as a measure of farm specialisation. Finally, the ratio of production subsidies to the total output (*Subsidies*) was included into the model to account for the accumulated public support. Note that the first three variables were mean-scaled in order to ensure a faster convergence of the maximum likelihood model.

The double bootstrap algorithm described in the preceding section was then employed for the analysis. The distribution of the efficiency scores is not discussed in this paper for sake of brevity. The numbers of the bootstrap replications were set as $L_1=100$ and $L_2=2000$.

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The first bootstrap loop aimed at estimating the bias-corrected output efficiency scores. For that purpose, each bootstrap replication aimed at obtaining the corrected output quantities (Step 3.3) and, subsequently, the bootstrap efficiency scores (Step 3.4). The plots of the bootstrap output quantities, y_k^*, against the original observations, y_k, for the first bootstrap replications indicate that a number of farms were attributed with augmented output quantities. Therefore, the reference technology set, $\hat{T}^*$, moved outwards.

The second bootstrap loop was used to estimate the confidence intervals for the parameters of the truncated regression. Analysis of the kernel distributions of the bootstrap estimates, $\hat{\hat{\beta}}^*$, obtained in Step 6 enabled to make a certain inference. Noteworthy, the densities for *Time* and *UAA* covered the value of zero, which, in turn, is associated with insignificance of a coefficient. The remaining densities lie in either side of the coordinate axis.

The regression was estimated without an intercept. The confidence intervals for the parameters of the truncated regression (Step 7) were estimated by both the percentile method and BC_a method. The resulting intervals are given in Table 1. Note that the dependent variable was the output-oriented Farrell efficiency score which gets higher values as farm becomes more inefficient. Therefore, the negative coefficients in Table 1 indicate sources of efficiency; whereas, the positive ones indicate factors negatively related with efficiency.

Table 1

Double bootstrap estimates for determinants of the farming inefficiency

Variables	$\hat{\hat{\beta}}$	Sig.	Confidence intervals					
			$\alpha = .1$		$\alpha = .05$		$\alpha = .01$	
BC_a method								
Time	-0.061	*	-0.113	-0.010	-0.122	0.002	-0.144	0.016
UAA	-0.154	***	-0.270	-0.051	-0.292	-0.033	-0.335	-0.002
Assets/AWU	-0.484	***	-0.634	-0.355	-0.666	-0.327	-0.722	-0.288
Crop	1.947	***	1.747	2.145	1.711	2.181	1.625	2.283
Subsidies	1.555	***	1.386	1.717	1.357	1.750	1.304	1.810
Percentiles method								
Time	-0.061	*	-0.113	-0.009	-0.121	0.002	-0.143	0.017
UAA	-0.154	*	-0.262	-0.046	-0.283	-0.029	-0.332	0.004
Assets/AWU	-0.484	***	-0.630	-0.348	-0.659	-0.323	-0.715	-0.279
Crop	1.947	***	1.752	2.149	1.713	2.187	1.631	2.288
Subsidies	1.555	***	1.387	1.721	1.359	1.753	1.306	1.816

Significance codes: '*' - 0.01, '**' - 0.05, '*' - 0.1**

Source: authors' calculations

The three variables, namely, ratio of assets to labour, crop share in the total output, and production subsidy intensity, remained significant at 1% level of significance irrespective of the method employed for estimation of the confidence intervals. Meanwhile, the farm size variable featured higher significance under the BC_a method. The time variable exhibited the same significance across both the methods. Indeed, the time trend was significant at the confidence level of 10%.

The negative coefficients associated with the time trend, farm size, and ratio of assets to labour indicate that these variables contributed to the increase in efficiency. Therefore, the efficiency was likely to increase during the research period given the remaining factors remained constant. The larger farms did also feature higher levels of efficiency. The latter finding might be related with both economies of scale and higher abilities for investment. The crop farms appeared to be less efficient if compared with livestock ones (the positive coefficient was observed for the corresponding variable). The production subsidies tended to decrease farming efficiency possibly due to lower incentives for adoption of innovative practices and market-oriented production.

The ordinary least squares (OLS) model was also specified in order to check the robustness of the obtained results. The OLS estimates are presented in Table 2. As one can note, the coefficients associated with the model variables were specific with the same signs as in case of the truncated regression. The differences in absolute values of the coefficients might be explained by different magnitude of the variables (for instance, ratio of asset to labour might feature higher variance even after mean scaling). Indeed, both the significance and absolute value of the *Assets/AWU* increased significantly in the truncated regression model.

Table 2

Ordinary least squares estimates

Variables	Estimate	SE	*t* value	*p*	Sig.
Time	-0.04138	0.01531	-2.703	0.00697	***
UAA	-0.05581	0.03191	-1.749	0.08053	*
Assets/AWU	-0.01825	0.02744	-0.665	0.50602	
Crop	1.91746	0.05759	33.293	2.00E-16	***
Subsidies	1.29016	0.06536	19.741	2.00E-16	***
R^2	0.8443	Adj R^2		0.8436	
F *p*-value	2.20E-16				

Significance codes: '*' - 0.01, '**' - 0.05, '*' - 0.1**

Source: authors' calculations

Obviously, the significance of the efficiency determinants varied across the truncated regression and OLS estimations. Particularly, the ratio of assets to labour was not significant in the OLS model, albeit it featured a negative coefficient. The crop and subsidy indicators featured the same significance in both cases. The time and farm size variables were significant at different levels of confidence depending on model type and method for confidence intervals. Therefore, the results yielded by the bootstrapped truncated regression can be considered as confident ones.

Conclusions

The truncated regression coefficients associated with the time trend, farm size, and ratio of assets to labour indicate that these variables contributed to the increase in efficiency. Therefore, the efficiency was

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likely to increase during the research period given the remaining factors remained constant. The large farms did also feature higher levels of efficiency. The latter finding might be related with both economies of scale and higher abilities for investment. The crop farms appeared to be less efficient if compared with livestock ones (the positive coefficient was observed for the corresponding variable). The production subsidies tended to decrease farming efficiency possibly due to lower incentives for adoption of innovative practices and market-oriented production.

Even though, livestock farming is declining in Lithuania, the findings of the paper imply that the latter type of farming exhibited higher efficiency. Indeed, the measures of efficiency are not observed by the farmers and make no impact upon them in the short run. Similarly, the relative measures of efficiency might not be directly linked to the absolute measures of profit which are the main factor affecting farmer decisions. However, the future agricultural policy should pay more attention for increasing the attractiveness and viability of the livestock farming.

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