The Measurement of Time-Varying Technical Efficiency and Productivity Change in Polish Crop Farms

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Abstract

The main aim of this study is to measure the technical efficiency and decompose total factor productivity (TFP) growth of Polish crop farms. The novelty of our contribution is threefold. First of all, our work contributes to research on agricultural performance of Central and Eastern European countries in the post-European Union accession period. Secondly, compared to previous studies, our study expands them by decomposition of total factor productivity growth for a specific sector based on a very extensive dataset, thus providing a more in-depth analysis of factors driving productivity growth. Thirdly, we have thoroughly explored the same data set by several different models, showing consequences of choosing a particular model. The empirical analysis is based on a balanced panel of farms, from 2004 to 2011, taken from the Farm Accountancy Data Network.

Findings show that the average technical efficiency was only 63%. The elasticity of production was highest with respect to materials and lowest with respect to area. The capital elasticity was statistically non-significant. We point out that this sector is characterized by increasing returns to scale, with estimates ranging from 1.05 to 1.3 for the majority of observations. Furthermore, the results show that TFP was slightly decreasing (on average by 0.067% per annum) over the entire period.

Key Words

stochastic frontier analysis; panel data; total factor productivity; agricultural policy

1 Introduction

The transition from centrally planned economy to market economy in the Central and Eastern European countries (CEEc) provoked many analyses of technical efficiency of the agricultural sector in these countries. A summary of the results of those studies is presented in GORTON and DAVIDOVA (2004). More recent findings can be found in BOJNEC and LATRUFFE (2013). However, a more complete assessment of the performance of agricultural sectors can be made basing on the total factor productivity (TFP) index. Generally, in the literature there are mainly studies on cross-country comparisons, e.g. BALL et al. (2001), BRÜMMER et al. (2002), TONINI and JONGENEEL (2006), BALL et al. (2010), SWINNEN and VRANKEN (2010), TONINI (2012), LATRUFFE et al. (2012), ČECHURA et al. (2014) and BARÁTH and FERTŐ (2017). The farm-level studies for a single country from Central and Eastern Europe are less common especially ones conducted in the post-European Union (EU) accession period, an exception is ČECHURA (2012).

We argue that a micro-level analysis gives the most in-depth analysis of the sector. Therefore, in the present study we have focused on one country and one sector. In particular, we have focused on Polish crop farms, since Poland plays an important role in the EU cereals market, being the third largest producer. Concerning the particular cereals, Poland was the fourth largest producer of wheat, second largest producer of rye, and fifth largest producer of barley in the EU in 2011 (CSO, 2012). Moreover, Poland was the second largest producer of potatoes in the EU.

Since the previous studies on Polish crop farms such as LATRUFFE et al. (2008a) were conducted in the pre-EU accession period, it is a crucial empirical task (considering the role of Polish crop production in the EU) to discover the rate and sources of productivity growth of Polish crop farms in the post-EU accession period.

The novelty of our contribution is threefold. First of all, our work contributes to research in agricultural performance of CEEc in the post-EU accession period. Secondly, compared to previous studies, our study expands them by decomposition of total factor productivity growth for a specific sector based on a very extensive dataset, thus providing a more in-depth analysis of factors driving productivity growth. In particular, we were able to distinguish farm profiles according to economic size and land size. This enabled us to indicate which profiles had the highest TFP growth, thus indicating which farms were most likely to develop further, and which were rather going to exit the sector. Thirdly, we have thoroughly explored the same data set by several different models, showing consequences of choosing a particular model.

The remainder of this paper is structured as follows. In Section 2 we present methods used to estimate the stochastic frontier model. In Section 3 we review the methods used to decompose productivity growth into its components. In Section 4 the data are described, and the empirical results are presented in Section 5. The paper concludes with a summary of the main findings.

2 Econometric Model

To measure farm-specific technical efficiency, we use stochastic frontier models, which were simultaneously introduced by AIGNER et al. (1977) and MEEUSEN and VAN DEN BROECK (1977).

The general stochastic frontier production function for farm i (i=1,…,N) in period t (t=1,…,T) can be formulated as follows:

$$y_{it} = h(x_{it}, \beta) + v_{it} - u_{it} \tag{1}$$

where y_{it} is the natural log of the observed output, h is a known production function (after logarithmic transformation), x_{it} is the vector of log of inputs used by the farm, β is a vector of k parameters, and v_{it} is a random error term with a mean of zero and constant variance σ_v^2, representing random shocks, $v_{it} \sim N(0, \sigma_v^2)$. Component $u_{it} \geq 0$ is referred to as inefficiency, and so the output-oriented technical efficiency score is calculated as $TE_{it} = exp(-u_{it})$.

The two most popular formulations that describe the time variation of inefficiency take the following form:

$$u_{it} = f(t) \cdot u_i, \tag{2}$$

where u_i is non-negative truncations of the $N(\mu, \sigma_u^2)$ distribution (BATTESE and COELLI, 1992). They differ in the form of $f(t)$, which determines how technical inefficiency term varies over time. KUMBHAKAR (1990) proposed a parametric sigmoid function of time $f(t) = (1 + \exp(\delta_1 t + \delta_2 t^2))^{-1}$, while in BATTESE and COELLI (1992) the parameterization of the function of time was formulated as:

$$f(t) = exp[-\eta(t - T)] \tag{3}$$

Both specifications have some limitations that the ranking of the firms does not change in successive periods. The firm classified first will be first also in the last period of the analysis. The generalisation of BATTESE and COELLI (1992) model that allows the temporal pattern of inefficiency effects to vary across firms was proposed by CUESTA (2000). A thorough review of recent advances in the stochastic frontier analysis is presented by GREENE (2008), KUMBHAKAR and TSIONAS (2011) as well as PARMETER and KUMBHAKAR (2014).

In the present study, we have utilized the time-varying inefficiency model introduced by BATTESE and COELLI (1992). They proposed estimating the model in a random effects framework using the maximum likelihood estimator. The log-likelihood function and its partial derivatives are provided in their paper. We used the truncated normal and half-normal models, described in detail by BATTESE and COELLI (1992), which we estimated using COELLI and HENNINGSEN (2013) package in R[1]. Thus the likelihood function for the reference model is parameterized by $\sigma_S^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2/\sigma_S^2$. In the half-normal model and cross-sectional data, γ is a useful indicator of the influence of the inefficiency component in the overall variance of the composed error term ($\varepsilon_i = v_i - u_i$) that is the difference between the observed output and the predicted frontier output (GREENE, 2008). Then, as γ tends to 0, the symmetric error dominates the one-sided component in the determination of ε_i. In the truncated normal model, these considerations about the meaning of γ are limited due to an additional location parameter (μ) of the inefficiency distribution.

Generally, the estimates of inefficiency are reasonably robust to model specification. According to GREENE (2008), since all results are application-specific, there is no analytical evidence as to what extent distribution for inefficiency term affects the results. In the present study, we consider two most commonly used distributions for the inefficiency term: truncated normal and its special case, i.e. half-normal. Moreover, we consider time-varying (u_{it}) and time-invariant specifications for the inefficiency ($u_{it} = u_i$ for every t). As a result, the frontier function, which is defined by Equations (1), (3) and (4), is estimated for four models. The most general is the first model in which the inefficiency terms have time-varying structure and have truncated normal distribution (i.e. η is an unknown, free parameter). Model 2 is the time-invariant version of the above model ($\eta = 0$). Model 3 is the special case of Model 1; in it, the u_{it} has half-normal distribution ($\mu = 0$). Model 4 is a special version of Model 3 with the assumption that efficiency is constant over time ($\eta = 0$ and $\mu = 0$).

[1] Additionally, we use own source code to calculate the production function characteristics.

Initially, we assume that deterministic part of all models is formulated as in (4). An additional model (M5) is obtained by imposing restrictions on the parameter space in model M1, i.e. $\beta_{j,trend}=0$ for j=1,...,4 in (4). Consequently, model M5 does not allow the parameters to vary over time. Most significantly, though, our model estimation has shown that both models M1 and M5 fit data very well, especially the first one (M1). More details can be found in Table 2 in Section 5.

The most popular functional form of the production frontier is a translog which belongs to the family of flexible functional forms (CHRISTENSEN et al., 1973). These functional forms are widely used in applied econometrics, including production and cost analysis. Translog is a second-order local approximation of any twice-differentiable function, and it is important that it satisfies the Diewert's minimum flexibility requirement for flexible forms. In this study, the deterministic kernel of the stochastic production frontier is given in the following translog form:

$$h(x_{it};\beta)=\beta_0+\sum_{j=1}^{J}\beta_j^{(t)}\cdot x_{it,j}+\sum_{j=1}^{J}\sum_{g\geq j}^{J}\beta_{j,g}\cdot x_{it,j}\cdot x_{it,g}+\beta_{trend}\cdot t,$$

$$\beta_j^{(t)}=\beta_j+\beta_{j,trend}\cdot t \;\; for \;\; j=1,\dots,K. \tag{4}$$

The translog form (4) with a linear trend in the parameters was used, among others, by COELLI et al. (2005) and KELLERMANN et al. (2011). The advantage of this form is that the elasticities with respect to factors and economies of scale may change over time. In the literature, the generalisation of this concept to a quadratic trend in the parameters was also considered by, among others, BATTESE and BROCA (1997) and KOOP et al. (1999, 2000).

In the empirical study presented below, production inputs are aggregated into four categories (J=4). To obtain clear interpretation of the parameters in (4), all variables were mean-corrected prior to estimation. Therefore, the first-order parameters in the translog function are interpreted as the output elasticities with respect to the inputs at the sample means (including time trend variable).

3 Measuring TFP Growth

The estimated stochastic production function with the time varying inefficiency can be easily used to measure Total Factor Productivity (TFP). The TFP index measures the change in total output relative to changes in the use of all inputs. The commonly used productivity index is the so-called Malmquist index introduced by CAVES et al. (1982). The first parametric decomposition of TFP change into technical efficiency change and technical change was presented by NISHIMIZU and PAGE (1982). They derived their TFP indices using derivatives. FÄRE et al. (1994) demonstrated that the Malmquist index can be obtained directly as the ratio of two distance functions in non-parametric framework using Data Envelopment Analysis. In their study, productivity index is decomposed into three components: technical efficiency change, technical change and scale efficiency change. The application of explicit distance measures was later adopted in parametric stochastic frontier approach by FUENTES et al. (2001) and OREA (2002).

In the present study, TFP growth is measured according to the method proposed by OREA (2002), who decomposed the TFP index into three components: Technical Efficiency Change (EC), Technical Change (TC) and Scale Change (SC). The Malmquist index used in this study is based on single output production technology (details of this case can be found in COELLI et al., 2005: 300-302). Other (generalized) approach was proposed by KOOP et al. (1999). The application of the extended latter approach to measure the productivity change in Polish dairy farms was presented in MAKIEŁA et al. (2017).

With reference to the approach presented by OREA (2002), the efficiency change (EC) captures the changes in technical efficiency from one period to the next. It is simply calculated from the technical efficiency terms obtained from the model, using the following rate Equation:

$$EC_{i,t/t+1}=exp\left(u_{i,t}-u_{i,t+1}\right)-1=\frac{TE_{i,t+1}}{TE_{i,t}}-1 \tag{5}$$

The technical change component characterizes the shift in best-practice technologies. It is derived from the geometric mean of the partial logarithmic derivatives of the production function with respect to time between adjacent periods t and t+1. Due to the fact that all economic variables are conveniently expressed in a logarithmic scale, we can use exponential transformation to compute an indicator of relative changes. In consequence, the rate of technical change is given by:

$$TC_{i,t/t+1}=exp\left[\frac{1}{2}\left(\frac{\partial y_{i,t+1}}{\partial t}+\frac{\partial y_{i,t}}{\partial t}\right)\right]-1 \tag{6}$$

In the case of translog production function given by (4), the partial derivative with respect to time is as follows:

$$\frac{\partial y_{i,t}}{\partial t} = \beta_{trend} + \sum_{j=1}^{J} \beta_{j,trend} \cdot x_{it,j} \quad (7)$$

Scale change measures the contribution of scale economies to productivity growth. The scale change (SC) component is calculated by aggregating inputs using elasticity shares (COELLI et al., 2005: 302):

$$SC_{i,t/t+1} = \exp\left[\frac{1}{2}\sum_{j=1}^{J} C_{i,t/t+1,\mathrm{j}}\left(x_{i,t+1,j} - x_{i,t,j}\right)\right] - 1 \quad (8)$$

where:

$$C_{i,t/t+1,j} = Elast_{i,t,j}\left(1 - \frac{1}{RTS_{i,t}}\right) + Elast_{i,t+1,j}\left(1 - \frac{1}{RTS_{i,t+1}}\right) \quad (9)$$

In the case of production function given by Equation (4), the elasticity with respect to the input *j* is given by:

$$Elast_{i,t,j} = \frac{\partial y_{it}}{\partial x_{it,j}} = \beta_j + 2\beta_{j,j} \cdot x_{it,j} + \sum_{h \neq j}^{H} \beta_{h,j} \cdot x_{it,h} + \beta_{j,trend} \cdot t \quad (10)$$

and, in consequence, the returns to scale coefficient is given by

$$RTS_{i,t} = \sum_{j=1}^{J} Elast_{i,t,j} \quad (11)$$

As it can be easily seen, the decomposition of SC presented above in Equation (8) allows to compare the technology of a farm against a benchmark technology satisfying constant returns to scale. It means that, in both periods, for a unit (farm) operating under constant returns to scale, SC rate is zero if each change in inputs satisfies this condition (RTS=1). It is easy to formulate other conclusions in the case of proportional change in inputs and established economies of scale in production.

The scale change rate is positive if, for example, a unit characterized by RTS_t>1 increases (in period t) the scale of production through a proportional increase in inputs. Then the coefficient of returns to scale will decrease, i.e. $RTS_{t+1} < RTS_t$, but if RTS_{t+1} is still greater than 1, thus SC indicator is positive. An analogous case occurs for a unit characterized by $0<RTS_t<\mathrm{RTS}_{t+1}<1$ when it is operating still under diminishing returns to scale in both periods and inputs are reduced proportionately. A negative value of SC is when RTS>1 and a farm reduces its activity (inputs are decreasing) or alternatively, if RTS<1 and the farm expands its activity (inputs are increasing), simultaneously. In other cases, it is not easy to draw clear conclusions about a change in SC.

4 Data on Polish Crop Farms

The dataset used for the analysis is taken from the Polish Farm Accountancy Data Network (FADN). It covers farms whose main source of revenue in the analyzed period was field crop production. The precise definition of the variables in the production function is based on other studies on the field crop sector in which FADN data were used (see ZHU and LANSINK, 2010; LATRUFFE et al., 2004). Therefore, the output (Q) is specified as deflated total net farm revenues from sales excluding the value of feed, seeds and plants produced within the farm. Agricultural production price indices (i.e. the market procurement prices of crop and animal provided by Central Statistical Office of Poland) are used as deflators. The four factors of production are defined as follows:

1. Physical capital (K) is measured in terms of deflated book value. It includes fixed capital such as buildings and fixed equipment, as well as machines and irrigation equipment. The aggregated measure of this input was deflated by the price index for agricultural machinery and equipment, and building construction.
2. Total labour (L) is measured in hours. This measure includes both hired and family labour declared by the farmer during the interview.
3. Total utilized agricultural area (A, in hectares) refers to owned and rented land.
4. Materials (M) consist of several subcategories: purchased feed, seeds and plants, fertilizers, crop protection, crop and livestock specific costs, energy and services. Originally, these subcategories are measured as the cost of resources used in farm production. In order to deflate the total reported expenditure on materials, we used price indices provided by the Central Statistical Office for each subcategory. The aggregate measure of materials is calculated by deflating total cost of all items with a share-weighted average price index constructed using the expenditure share for all the components. Furthermore, we excluded the value of seeds and feed produced within the farm from this category to avoid double measuring these costs.

The stochastic frontier models of the Polish farms specialized in field crops were estimated using the yearly data set covering a sample of 660 farms between 2004 and 2011. The summary statistics for farms in the sample are presented in the Table 1. The

Table 1. Descriptive statistics for variables in the sample

Variable*	Mean**	Percentile		
		25th	50th	75th
Output ('000 PLN)	122	63	118	233
Capital ('000 PLN)	232	124	232	431
Labour (in hours)	4,056	2,900	3,938	5,214
Materials ('000 PLN)	84	42	78	150
Land area (in ha)	43	21	40	83

*Figures in PLN were deflated (with base year 2004).
**Descriptive statistics for output and input variables were calculated on the logarithmic scale and then back transformed to the original scale.
Source: authors' calculations

average area of land per farm is 43 hectares. However, since FADN data are biased toward larger farms, the average area per farm is in fact smaller. It amounted to 8.4 hectares in 2011 (CSO, 2017). To conclude, it means that Polish farms are small, especially in comparison to those from Western Europe. ZHU and LANSINK (2010) reported that the average land area per owner is 163 ha in German, 71 ha in the Netherlands, 115 ha in Sweden, and 142.9 ha in France (LATRUFFE et al., 2012). Crop farms in CEEc are also much larger than in Poland, for instance in the Czech Republic the average utilized agricultural area is 144 ha (LATRUFFE et al., 2008b), while in Hungary it is 226.4 ha (LATRUFFE et al., 2012). Slovenian farms are similar in size to Polish farms, with an average land size of 20 ha (BOJNEC and LATRUFFE, 2013).

According to the data from the farm accounts, we could establish that the average yearly income from selling crops was 2.959 PLN per hectare approximately 696 euros per ha. Moreover, the average labour productivity of Polish crop farms was 43.2 PLN (10.2 euros) per hour. It is noteworthy that in 2004 GDP per hour worked was 30.2 euros in the present European Union member states (28 countries), and only 7.2 euros in Poland, whereas in 2011 this indicator reached 35 and 12 euros in these regions, respectively (see PORDATA, 2017). Moreover, the latter indicator obtained from the sample data is convergent with a measure of an economy competitiveness published in official statistics publications. Furthermore, it also means that labour productivity in Poland is still very low compared to the EU average and this also applies to agriculture.

5 Estimation and Testing of Stochastic Frontier Models

Table 2 shows ML estimation results for the parameters of the stochastic components of the stochastic frontier production function (1). Five models are evaluated in two ways: by comparing across models to determine which ones best fit the data in terms of the likelihood function, and by calculating Akaike's

Table 2. Estimates of disturbance distribution parameters (error term and inefficiency component)

Parameter	Model*				
	M1	M2	M3	M4	M5
η	-0.042 (0.007)	-	-0.049 (0.008)	-	-0.044 (0.006)
μ	0.543 (0.092)	0.466 (0.055)	-	-	0.551 (0.14)
σ_S^2	0.133 (0.014)	0.114 (0.007)	0.265 (0.018)	0.208 (0.011)	0.135 (0.016)
γ	0.555 (0.041)	0.476 (0.031)	0.773 (0.017)	0.707 (0.017)	0.562 (0.043)
σ_u^2	0.074 (0.013)	0.054 (0.007)	0.205 (0.019)	0.147 (0.011)	0.080 (0.015)
σ_v^2	0.059 (0.001)	0.060 (0.001)	0.060 (0.001)	0.061 (0.001)	0.059 (0.001)
Average TE	0.632	0.634	0.752	0.750	0.630
lnL	-708.1	-724.8	-714.1	-734.1	-715.8

*M1 - truncated normal model with time-varying efficiency, M2 - truncated normal model with time-invariant efficiency, M3 - half-normal model with time-varying efficiency, M4 - half-normal model with time-invariant efficiency, M5 - simplified version of model M1 without a time trend in the parameters ($\beta_{j,trend} = 0$ for every j).
Source: authors' calculations

Table 3. The likelihood-ratio test for model selection

Model	Number of parameters	Degree of freedom	LR test statistic	p-value	Akaike's criterion	Rank by AIC
M1	24	-	-	-	1464.1	1
M2	23	1	33.4	$7.4{\cdot}10^{-9}$	1495.6	4
M3	23	1	12.1	$5{\cdot}10^{-4}$	1474.2	3
M4	22	2	52.0	$5{\cdot}10^{-12}$	1512.1	5
M5: M1 with $\beta_{j,trend} = 0$	20	4	15.5	$3.7{\cdot}10^{-3}$	1471.7	2

Source: authors' calculations

Information Criterion (AIC) for each model; see Table 3. Therefore, the choice of the best model is made by testing statistically the reduction in log likelihood between five models. We compare relative strength of the models using a likelihood ratio (LR) test. For example, when testing M1 and M5 we find that the LR test statistic equals 15.5, and so exceeds the critical value at not less than the $3.7{\cdot}10^{-3}$ level of significance. This shows that the differences between models M1 and M2, M3 or M4 are significant at the 1% level. Therefore, the most general model M1 is the preferred one. It seems to prove that one additional parameter μ is important in explaining the similarities and differences between the considered models.

These results are confirmed by AIC, which is a criterion for selecting among both nested and non-nested models. It also shows that, out of the remaining four models tested, the non-nested model M5 provides a better fit than the three others and all are considered better than the half-normal model with time-invariant efficiency (M4). Comparison of model M5 against models M2 and M4 shows that the linear trend in the parameters is generally less preferred than the time varying efficiency and truncated normal distribution of the inefficiency term.

Additionally, we have also considered Cobb-Douglas version of model M5, restricting some parameters in β, i.e. $\beta_{j,g} = 0$ for every g and j. The restricted log-likelihood equals −777.82, and the AIC value is 1575.6. Therefore, this linear homogeneity restriction on translog is strongly rejected by the data.

Regarding the estimation of the error components (including the inefficiency term), it can be seen that the results from Table 2 indicate that parameter γ is strongly statistically significant in all models considered. Therefore, the presence of technical inefficiency leads to a decrease in crop production, which in turn requires fewer inputs to be used.

The results of efficiency estimates presented in Table 2 require further explanation. First of all, it should be noted that the technical efficiency scores are different across models. Secondly, it appears that the estimated efficiency scores obtained on the truncated normal frontier models (M1, M2, M5) are clearly smaller than those based on the half-normal models (M3 and M4). It is noteworthy that the truncated distribution of time-invariant firm effects u_i is characterized by two parameters. In the former models, the average technical efficiency estimate over the eight-year period is approximately only 63%, while in the latter models (M3 and M4) it is about 75%. These findings contradict the results obtained for example by GREENE (2008), who showed that inefficiency estimates are robust to model specification. Consequently, it is vital to explain the most probable cause of such a result. Further examination of the results suggests that the form of the production function and the assumption of time-varying or time-invariant efficiency do not affect the differences in efficiency scores. Therefore, the source of differences in efficiency estimates between the considered models may be the type of distribution chosen for the inefficiency error. This explanation is supported by the results of RITTER and SIMAR (1997), who found that free-shaped models (such as truncated normal or gamma) may lead to an imprecise estimate of shape parameter and a loss of precision regarding quantities of interest, e.g. the individual inefficiencies. It must be noted that in the truncated normal model for $\mu > 0$ the shape of density function of the inefficiency term is different from that in the half-normal case ($\mu = 0$). Since the estimates of parameter η are very similar in both models (M1 and M3), the features of the distribution of u_i are easier to compare between these models. In model M1, the estimate of μ equals 0.543 (±0.092), then it is relatively much larger than zero. As a result, it suggests that the raised estimates of inefficiency may be affected by the high value of μ. It is noteworthy that, considering a truncated normal distribution with a high estimate, μ makes the shapes of densities v_{it} and u_{it} hardly distinguishable. Consequently, in this empirical study the random component, u_i, may capture partly statistical noise. By comparing the results of the estimation described in Table 2, we find that estimated variance of disturbance term, v_{it}, is almost identical in all models. Moreover, the high estimate of μ causes the validity of model M1 in terms of the log-likelihood value. These results may suggest that u_i is poorly identifiable due to relations between v_{it} and u_{it}. Therefore, as pointed out by RITTER and SIMAR (1997), the usage of relatively simple distributions, such as half-normal or exponential is more preferred than more flexible distributions such as truncated normal or gamma, because they allow to avoid identification problems. They also indicate that the ranking of firms is not affected by distribution choice. Our results support that finding because the linear correlation of the efficiency estimates based on M1 and M3 are 0.98 for every period. Spearman rank correlation coefficient equals 0.99, which suggests that the efficiency rankings would be quite similar in these models. This finding is also in line with the results of KUMBHAKAR and LOVELL (2000: 90) who reported the highest correlation coefficient between half-normal and truncated normal efficiency estimates.

Moreover, the estimated expectation value (mean) of u_i is equal to 0.558 (with variance equal to 0.065) in M1 and 0.362 (with variance 0.075) in M3 (see formulas A5 and A6 in BATTESE and COELLI, 1992). It is quite apparent that in model M1 distribution for the inefficiency term is shifted to the right compared to the latter. Therefore, it explains the significant differences in efficiency scores obtained from the two models, and thus clarifies the fact that the estimated inefficiencies suggest that the restricted model M3 produces much smaller values for the inefficiencies than the more general truncated distribution.

Since inefficiency is inherently unobservable, there is a substantial difficulty in identifying it in empirical studies. Therefore, estimates of inefficiency must be derived indirectly. It seems that the choice of the distribution for the unobserved inefficiency poses an ongoing challenge in the classical literature. VAN DEN BROECK et al. (1994) showed that a Bayesian stochastic frontier model is theoretically and practically useful, and feasible. They pointed that the difficult choice of a particular sampling model for the inefficiency error term could be avoided by mixing over different models, reflecting the spectrum of distributions proposed in the literature. This study considered several prior distributions for inefficiency including half-normal and truncated normal, exponential, and the Erlang distributions.

Table 4 shows the variation of technical efficiency (TE) scores over time in models with time-varying efficiency. The estimate of η is always significantly greater than zero, and hence the average TE score is decreasing over time. In particular, in model M1 it declined from its peak of 0.67 in 2004 to less than 0.59 eight years later. For comparison, LATRUFFE et al. (2004) reported a similar average technical efficiency (0.73) for Polish crop farms in 2000, but they considered a model for cross-sectional data.

Table 4. Average farm-level technical efficiency (TE) estimates

Year	M1 (truncated with time-varying efficiency	M3 (i.e. M1 with μ=0)	M5 (M1 with $\beta_{j.trend}$=0)
2004	0.67	0.78	0.66
2005	0.66	0.77	0.65
2006	0.65	0.77	0.64
2007	0.64	0.76	0.63
2008	0.63	0.75	0.62
2009	0.62	0.74	0.60
2010	0.60	0.73	0.59
2011	0.59	0.72	0.58
Average	0.63	0.75	0.62

Source: authors' calculations

6 Modelling Production – Empirical Results

Table 5 gives information about the production function characteristics of a typical crop farm (with average values of logs of the inputs). It is interesting to note that all estimated elasticities except the first one are highly statistically significant at the 1% level and are positive as expected. The elasticity of production with respect to capital turned out to be statistically non-significant and quite small in our models, i.e. it was close to zero and slightly negative, but only in models M1 and M3. The results of the estimation indicate that the basic regularity conditions of the underlying production frontier are satisfied. Further examination shows that about half (52%) of the farm capital elasticities (in the sample) is slightly below zero. In other cases, the elasticities invariably have the expected signs. These results show that the highest is the elasticity of production with respect to materials, while the lowest are the elasticities with respect to area and capital. Furthermore, during the period 2004-2011, technical progress in crop production was significant only in models M1 and M5. These results are in line with findings of ČECHURA et al. (2014) who also found that crop farms in the European Union show the highest elasticity for materials, and the lowest for capital. However, ČECHURA et al. (2014) found technical regress for Polish crop farms. The low capital elasticity can be explained according to ČECHURA et al. (2014) by limited access to credit and usage of old machinery by farmers. This can be the case of Poland because, as indicated by CIAIAN et al. (2011), Polish farms are credit constrained. The second cause of low elasticity of capital is also possible since, as LORENCOWICZ and UZIAK (2015) pointed out, the average age of a tractor is more than 23 years. Furthermore, they noted that owners of small farms do not invest in new machines, using their machines even for 40 years.

In the period under investigation, a typical Polish crop farm was characterized by increasing returns to scale, which is approximately 1.16 (±0.01). Further examination indicates that only 2.9% of the farms had decreasing returns to scale. Therefore, almost all units had non-diminishing returns to scale and even 49% operated under increasing returns to scale greater than 1.16. This result is in line with that of LATRUFFE et al. (2005), who reported that 86% of crop farms had an increasing RTS in 2000. We found that 87% of observations were characterized by increasing returns to scale ranging from 1.05 to 1.3. Less than 3% of them had RTS greater than 1.3. This high value of RTS can be explained by relatively small size of Polish farms. ČECHURA et al. (2014) formulated the same conclusion for crop farms in Austria, Germany, Denmark, France, the United Kingdom, Ireland, the Netherlands, Poland and Slovakia.

It is noteworthy that estimates of returns to scale evidently vary across units, making the Cobb-Douglas model inadequate to describe crop production in Poland. The hypothesis of constant returns to scale is rejected as well.

Table 6 shows that elasticities with respect to labour and area are approximately constant in the period 2004-2011. It can be seen that the only noticeable change concerns elasticities with respect to two inputs: capital and materials. The average elasticity with respect to capital was decreasing, while material

Table 5. Production elasticity estimates and returns to scale (RTS) at sample mean for inputs* (standard errors in parentheses)

Elasticity w.r.t.	Model				
	M1	M2	M3	M4	M5
Capital	-0.001 (0.012)	0.004 (0.013)	-0.001 (0.012)	0.001 (0.012)	0.012 (0.013)
Labour	0.273 (0.015)	0.275 (0.014)	0.286 (0.014)	0.286 (0.014)	0.277 (0.014)
Materials	0.679 (0.018)	0.683 (0.017)	0.664 (0.017)	0.665 (0.017)	0.668 (0.017)
Area	0.206 (0.015)	0.199 (0.014)	0.195 (0.014)	0.191 (0.014)	0.206 (0.017)
RTS	1.157 (0.014)	1.160 (0.014)	1.144 (0.014)	1.143 (0.014)	1.163 (0.017)
Time	0.017 (0.004)	-0.005 (0.003)	0.001 (0.003)	-0.006 (0.003)	0.018 (0.005)

*Inputs equal to the arithmetic mean of the data on a logarithmic scale.
Source: authors' calculations

Table 6. Average estimated elasticity of production for the yearly period (model M1)

Year	Elasticity					RTS
	Capital	Labour	Materials	Area	Time*	
2004	0.036	0.277	0.648	0.197	0.016	1.158
2005	0.026	0.279	0.653	0.202	0.016	1.160
2006	0.015	0.276	0.666	0.201	0.017	1.158
2007	0.006	0.273	0.672	0.204	0.018	1.156
2008	-0.006	0.269	0.683	0.209	0.018	1.155
2009	-0.020	0.269	0.695	0.212	0.017	1.156
2010	-0.029	0.273	0.702	0.211	0.018	1.157
2011	-0.040	0.269	0.714	0.212	0.018	1.154
Average	-0.001	0.273	0.679	0.206	0.017*	1.157

* Time trend elasticity is calculated as a geometric mean.
Source: authors' calculations

Table 7. Decomposition of TFP growth in Polish crop farms (in percentages, model M1)

Years	Efficiency Change	Technical Change	Scale Change	TFP growth
2004/2005	-1.753	1.638	0.101	-0.015
2005/2006	-1.827	1.674	0.307	0.153
2006/2007	-1.904	1.737	0.214	0.047
2007/2008	-1.984	1.785	0.053	-0.146
2008/2009	-2.068	1.770	0.041	-0.257
2009/2010	-2.155	1.764	0.426	0.035
2010/2011	-2.245	1.809	0.153	-0.282
Average	-1.991	1.739	0.185	-0.067

Source: authors' calculations

elasticity was increasing in the investigated period. This result is consistent with the test results concerning the evaluation of model fit, which shows that the model with time-varying elasticities is more preferred than the model with time-invariant elasticities (M5). In addition, in each period, increasing returns to scale were observed for almost all of the farms.

Table 7 reports the annual decomposition of TFP growth together with an overall yearly average and seven sub-period averages for the crop farms. The components of productivity growth are measured in percentages, i.e. Equations (5), (6) and (8) are multiplied by 100%. The results show a decrease in total factor productivity rather than positive TFP growth rates. Over the entire period, negative growth was more common than positive one. As a result, it can be seen that TFP was slightly decreasing (on average by 0.067% per annum) over eight years. Therefore, this value was close to zero, so the negative growth of productivity was very weak. This is primarily attributable to strong negative technical efficiency change, which is not compensated by positive technical change and scale effect in every period.

The result of further analysis shows that technical change (*TC*) was positive over the entire period, while technical efficiency change was negative over the entire period. The average annual growth rate of production due to the technical change is increasing over time and, on average, equals about 1.7% annually. Similarly, ZHU and LANSINK (2010) reported an increasing positive technical change from 1995 for crop farms in Sweden (which joined EU in 1996).

Productivity growth rate due to the change in efficiency score equals minus 2%. The decreasing technical efficiency change can be partially explained by the impact of Common Agricultural Policy subsidies, which were shown in many studies to negatively affect technical efficiency (see ZHU and LANSINK (2010), MARZEC and PISULEWSKI (2017)).

The presented results concerning the decomposition of TFP show, similarly as LATRUFFE et al. (2008a) findings for the pre-accession period, a decline in productivity growth. However, in that study the decline of productivity was mainly caused by negative technical change, while in our study it is attributed to negative technical efficiency change.

Moreover, the conducted micro-level analysis reveals a different picture of Polish crop farm sector than from international comparisons. In particular, our finding contradicts the results obtained by ČECHURA et al. (2014), who showed an increase in TFP for Polish crop farms in the post-EU accession period (average TFP rate equals to 0.28%). However, the different result might be caused by the different methodologies of TFP measurement. Furthermore, the obtained results show the opposite development of the farms on micro-data level than in the other CEE countries; e.g. ČECHURA (2012) reported a TFP growth for plant production sector in the Czech Republic in the 2004-2007 period.

In the present study, we also conducted a profound analysis to explain the TFP decrease, dividing the considered farms according to economic size (*ES*) and utilized agricultural area (UAA). Size groups with respect to income level (i.e. output of crops and crop products) are defined as: small (2≤ *ES*<25 thousand euros), medium and large (≥100 thousand euros).

Table 8 shows that small farms have a negative TFP growth rate and large farms are characterized by positive TFP. The results of the in-depth analysis show that the source of these differences in TFP is, above all, the higher technical efficiency (*TE*) of larger units. During the period considered, the mean *TE* score was 0.69 for large farms, 0.67 for medium, and only 0.59 for small units. Thus, there were clear economic differences between two extreme groups. In 2011, the large farms accounted for only 11% of the surveyed units, while the share of the small ones was

Table 8. TFP growth in Polish crop farms of different economic size (in percentages, model M1)

Years	Economic size (ES, in thousand euros)		
	2≤ ES <25	25≤ ES <100	ES ≥ 100
2004/2005	-0.60	0.32	1.04
2005/2006	-0.14	0.40	0.51
2006/2007	-0.31	0.29	0.78
2007/2008	-0.74	0.20	0.76
2008/2009	-0.90	0.27	0.61
2009/2010	-0.37	0.40	0.34
2010/2011	-0.98	0.13	0.38
Average	-0.58	0.29	0.63

Source: authors' calculations

40%. Consequently, 60% of the farms had positive productivity growth in 2004-2011.

Table 9 reports the results based on the second grouping scheme. The farms were divided into four groups according to utilized agricultural area. The differences in TFP growth between these groups were smaller than between groups stratified according to ES. This is partly due to the fact that we considered the most detailed grouping of the units. However, the nature of dependence is qualitatively the same. Similar results were obtained by LATRUFFE et al. (2008a), who showed that best-performing are farms with the largest average land size.

7 Conclusions

In the present study we have considered a number of competing model specifications, among which there are the truncated normal model with time-varying efficiency and its simpler variants. The latter are obtained by imposing restrictions on the structure of the reference model. Likelihood ratio test and Akaike's information criterion indicate that the most general model is the preferred one. Subsequently, we obtain the mean efficiency for each considered model, discovering that it differed significantly between the models. Substantial differences were especially apparent between truncated normal and half-normal model specifications. While the former indicates a mean technical efficiency of 63%, the latter suggests that the mean technical efficiency is higher, i.e. 75%. At the same time, efficiency scores in both models were decreasing over time during the eight-year study period. From the agricultural policy point of view it implies that organization of production requires considerable improvement. However, discovering the exact cause of decreasing technical efficiency scores requires in-depth analysis in the future. Further examination of the results reveals a high Spearman rank correlation coefficient between technical efficiency scores in both models. Therefore, the rankings of farms are very similar or even identical in both cases. From these results, we can draw the following conclusion. Due to identification problems, application of relatively simple distributions, such as half-normal or exponential, is more preferred than more flexible distributions, such as truncated normal or gamma, especially since the ranking of farms is unaffected by distribution choice.

Concerning the properties of production technologies, it should be noted that low production elasticity with respect to capital can be caused by limited access to credit and by the use of old machinery by farmers. Moreover, the returns to scale remain largely unchanged over the eight-year period of the analysis. The mean of the estimates equals approximately 1.16, so the hypothesis of increasing returns to scale cannot be rejected based on the obtained results.

Furthermore, we decomposed the productivity growth, basing on results derived from truncated

Table 9. TFP growth in Polish crop farms of different utilized agricultural area (in percentages, model M1)

Years	Utilized agricultural area (UAA in ha)			
	0 ≤ UAA < 20	20 ≤ UAA < 50	50 ≤ UAA < 100	UAA ≥ 100
2004/2005	-0.04	-0.03	-0.17	0.28
2005/2006	0.42	-0.05	0.16	0.20
2006/2007	-0.66	0.22	0.18	0.50
2007/2008	-0.04	-0.41	-0.09	0.20
2008/2009	-0.02	-0.61	-0.30	0.18
2009/2010	-0.16	0.12	0.10	0.03
2010/2011	-1.03	-0.18	-0.11	0.13
Average	-0.22	-0.13	-0.03	0.22

Source: authors' calculations

normal with time-varying efficiency model. The results show a decrease in total factor productivity for crop farms in Poland. Taking into account that Polish agriculture receives substantial support under Common Agricultural Policy, the falling productivity is a surprising finding. The decomposition of total factor productivity reveals that the main factor contributing to this effect is strong negative technical efficiency change, which is not offset even by strong and positive technical change and positive but small scale change. On one hand, the positive technical change and scale change suggest that in the investigated period Polish crop farms acquired new technologies and adjusted their size to the most productive. On the other hand, the use of inputs in the crop farms is under optimal, significantly affecting the TFP index. This is an undesirable phenomenon since it hampers the development of competitiveness of Polish farms.

The thorough analysis of differences in total factor productivity among distinguished economic size groups revealed that medium and large farms are more technically efficient than small farms and recorded a higher productivity growth. Therefore, the existence of small farms, which is connected with the highly fragmented structure of Polish agriculture, seems to have no positive effect on productivity growth in Poland. Furthermore, grouping farms according to utilized agricultural area resulted in similar conclusions. In summary, both criteria, according to which the farms were divided, are found to lead to convergent conclusions. The development of large and medium farms is well-founded from the point of view of economic benefits, especially as we found earlier that these units have increasing returns to scale.

This analysis might lead to the conclusion that productivity improvement in crop production is more dependent on larger farms than the smaller ones. The above empirical evidence seems to be important from the decision-makers' point of view if it is to influence the path of agricultural development in Poland. The economic transformation process leads to higher labor costs, which in turn drives most small farms out of business (HAZELL, 2005). Therefore, from the agricultural policy perspective, the challenge is to enhance productivity of small farms in Poland. However, discovering exact factors that increase survival probability of small farms needs further research based on different econometric models and data than those used in the present study.

The results presented above seem to be interesting from a practical point of view, but they were obtained from the well-known models. Our current study is based on the concept of production function, so it has many limitations, e.g. there is only one product as output and all production inputs are treated as fixed. Applications of a cost function-based analysis of productivity and efficiency will be the subject of next research. Another important problem is unobserved heterogeneity across farms, which is very large in Poland because they are characterized by a high farm land fragmentation rate. Therefore, future research requires more advanced approaches (e.g. BARÁTH et al., 2018). In panel data analysis, unobserved heterogeneity can be statistically modelled by mixture (or mixed) models. A way to take into account the heterogeneity is to use Bayesian hierarchical models.

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