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DIFFERENCES IN EFFICIENCY AND PRODUCTIVITY BETWEEN CONVENTIONAL AND ORGANIC FARMS: THE CASE OF HUNGARIAN CEREAL OILSEED AND PROTEIN (COP) CROP PRODUCING FARMS (2010-2015)

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ABSTRACT
The aim of this paper is to compare technical efficiency (TE) and total factor productivity (TFP) of Hungarian organic and conventional Cereals, Oilseed and Protein (COP) crop producing farms. We model production with a random parameter stochastic production frontier model, which allow us to consider technological differences among farms. Based on the estimated parameter of the model we construct Törnquist-Theil TFP index. We compare TE and TFP between the analysed groups using statistical tests, then in order to account for selection bias we use matching method to compare these performance indicators. Results show that both TE and TFP scores of organic farms are smaller compared to conventional farms, but the difference is statistically not significant.

KEYWORDS:
efficiency, productivity, organic farms, conventional farms, Hungary, cereals, oilseed and protein producing

INTRODUCTION

Organic production and its importance have increased over the past decade along with rising consumer demand for the product in the EU.
However, there is a solid understanding of the drivers, such as technical efficiency (TE) that influence the competitiveness of organic farming. Due to the regulations that define and govern organic farming, organic production systems differ from conventional systems, and are subject to different relative scarcities. Production economists have typically compared cost and/or profitability of production systems in one of several ways: cost and return estimates, regression analysis, production frontiers. There are some studies comparing costs of organic and non-organic production like [2] where the highest costs were for organic grain-fed, followed by organic grass-fed, and finally conventional grain-fed production in the US beef sector.
In [9] article sets out to investigate the development of total factor productivity in organic and conventional agriculture from 1999/2000 to 2006/07. Malmquist Indices based on Stochastic Frontier Analysis was used to estimate productivity development and the analysis is based on a balanced panel of farm records of 151 organic and conventional farms, respectively. The study reveals a similar development of productivity in organic grazing livestock and mixed farms, but the productivity level is still lower compared to their conventional farms. Only

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organic arable farms had started with a higher level of productivity in 1999/2000 but they were not able to maintain their advantage over their conventional counterparts. Lack of technical and scale efficiency are rather to be seen as the key drivers of the slowed productivity development in organic agriculture.

[5] also compared productivity and technical efficiency of organic and conventional dairy farms in the United States by using propensity score matching. Based on their results they reject the homogeneous technology hypothesis and found that the organic dairy technology is approximately 13% less productive.

[4] also analyse the efficiency of organic pasture farming in Germany. Five inputs and one output are analysed by means of a stochastic frontier production function, allowing for heteroscedasticity and technical effects. Regional effects are found to have a significant impact on the technical efficiency of organic farms. The evolution of efficiency on farms that are converting from conventional to organic farming is also analysed.

[10] examine scale efficiency using more than 650 cross-sectional data organic and conventional cocoa farmers in Ghana. Their results show that organic production is less scale efficient than the traditional ones. Besides the organic producers need to improve their farm management skills and input allocation.

[11] compare economics, financial (net return on assets, input cost) and productivity performances of organic and conventional dairy farms in USA from 2016. A stochastic production model was used to examine technical efficiency, return to scale of farms compared to production system and size category. Based on their results the size is the most determinant competitiveness factor in both production system. In the case of organic farms the pasture requirements may be also a limit to expand their productivity.

The aim of this paper is to compare efficiency and productivity of Hungarian organic and conventional field crop producing farms. More precisely, according to the FADN *types of farm* classification (TF14), we analyse farms, which are classified as specialists Cereals, Oilseed and Protein (COP) crop producing farms (Grouping Nr. 15 in the TF14 classification system).

Field crop production has traditionally been a key sector in Hungarian agriculture. About 40% of all Hungarian farms specialise in field crop production and use 60% of the arable land and account for more than a third of the output of agricultural production [6]. This is the subsector of Hungarian agriculture that integrates well with international commerce, in that the product channels are well organised, and the products comprise the largest proportion of agricultural exports [6].

For purposes of empirical examination, we use Hungarian national FADN Data over the 2010-2015 period.

First, we estimate Stochastic Frontier Models in order to examine production technology and technical efficiency (TE) of farms. In order to consider differences in production technology we apply a random parameter stochastic frontier model. Second, based on the estimated parameters we construct transitive Törnquist-Theil total factor productivity (TFP) index, which enable multilateral comparison of group of farms. Third, in order to eliminate potential selections bias between the analysed groups of farms we compare the TE and TFP scores of organic and conventional farms applying propensity score matching.

The structure of the paper is as follows. In the next section, we describe the database and variables used for the analysis. It will be followed by the description of the applied methodology then we report the results and discussion of the results, finally we conclude.

Data

For the empirical analysis, we used data from the Hungarian Farm Accountancy Data Network (FADN). The Hungarian FADN system contains data from about 1900 annually reporting agricultural farms. For the purpose of estimation, one output (Y – total agricultural production in value) and four inputs (labour in Annual Work Units (X_1), utilised agricultural area (UAA) in hectares (X_2), total fixed assets in value (X_3) and total crop specific costs consumption in value (X_4) were used. Additionally, a time variable (t) and time-squared variable (tt) were added to the production frontier to allow for non-monotonic technical change.

Table 1. Descriptive statistics

	Mean	Standard Deviation	Minimum	Maximum	Observation
Conventional					
Output(Y)	200619.6	315238.9	687.4	3664902.0	2968
LABOUR (X_1)	3.2	5.7	0.0	64.9	2968
LAND (X_2)	227.3	323.4	6.5	2398.0	2968
Capital (X_3)	302797.3	339429.7	242.5	3439738.7	2968
Materials (X_4)	65746.8	104290.2	425.9	1016633.8	2968
Organic					
Output(Y)	183395.8	85088.9	65536.0	308916.0	6
LABOUR (X_1)	2.0	1.0	0.8	3.4	6
LAND (X_2)	147.7	18.0	111.0	155.0	6
Capital (X_3)	120640.0	21880.1	93042.9	150403.1	6
Materials (X_4)	5706.6	2291.6	4101.6	10282.7	6
All farms					
Output(Y)	207223.6	339948.9	687.4083	3664902	3000
LABOUR (X_1)	3.400625	6.491146	0.01	76.6558	3000
LAND (X_2)	233.8631	345.1116	6.51	2859.61	3000
Capital (X_3)	306723.4	350264.3	242.4732	3439738.7	3000
Materials (X_4)	68627.2	120697.9	425.9439	1578782.5	3000

Source: Own calculation based on FADN data

All of the variables expressed in nominal prices were deflated to 2010 prices with the use of the appropriate deflators reported by the Hungarian Central Statistical Office (HCSO); precisely the output (Y) was deflated by the agricultural output price index, the intermediate consumption (X_4) by the price index of purchased goods and services and the corresponding values of total fixed assets (X_3) by the price index of agricultural investments.

We used a balanced panel, in order to ensure the comparison between the same farms over the years analysed. The total Number of COP producing farms was 3000 over the analysed period. The number of organic farms was low; we had only 6 organic farms. The number of conventional farms was 2968; 6 firms was converting to organic production methods and 20 farms applied both organic and conventional production method. Descriptive statistics of the variables are included in Table 1.

The variance is high for all of the variables, suggesting that heterogeneity plays an important role in the case of Hungarian COP producing farms and therefore it is important to account for it in the production model.

Method

We model production technology with an SFA model. Traditional frontier models assume that all firms face common technology. However, in practice firms use different technologies for a variety of reasons [9].

As the main goal of this paper is to compare organic and conventional farms and these groups of farms certainly use different technologies, we apply a random parameter model (RPM) which allow us to consider technological differences among farms.

The random parameter model (RPM), following [3], may be written as follows:

$$y_{it} = \alpha_i + \boldsymbol{\beta}_i'\boldsymbol{x}_{it} + \beta_{ti}t + v_{it} - u_{it}, \qquad (1)$$

where

$v_{it} \sim N[0, \sigma_v^2]$, $v_{it} \perp u_{it}$

$$u_{it} = |U_{it}|, U_{it} \sim N[0, \sigma_u],$$
$$\alpha_i = \bar{\alpha} + \alpha_w w_i,$$
$$\boldsymbol{\beta}_{xi} = \bar{\boldsymbol{\beta}}_x + \boldsymbol{\beta}_{xw} w_i,$$
$$\beta_{ti} = \bar{\beta}_t + \beta_{tw} w_i, \text{ where}$$

, i=1,…,N indicating the number of farms; t=1,…,T indicating the time period, w is an unobservable latent random term; α_i, $\boldsymbol{\beta}_{xi}$, β_{ti}, α_w, $\boldsymbol{\beta}_{xw}$, β_{tw} denote the parameters to be estimated, u_{it} represents technical inefficiency, and v_{it} stands for statistical noise [3] y_{it} represents the output variable and $\boldsymbol{x}_{it}$ are inputs.

Furthermore, based on the estimated parameters of the RPM, we constructed multilateral-consistent Törnquist-Theil TFP index [1]. This productivity index between farm i in period t and the sample average can be formulated as follows:

$$\ln \mathrm{TFP}_{it}^{TTI} = \left(\ln y_{it} - \overline{\ln y}\right) - \frac{1}{2}\sum_k \left(S_{kit} + \overline{S_k}\right)\left(\ln x_{kit} - \overline{\ln x_k}\right) \quad (2)$$

, where $k = 1, \dots, K$ inputs; and S stands for share of inputs. A bar above a variable refers to the arithmetic mean of the variable over all sample observations.

Moreover, a simple comparison of the performance indicators between organic and conventional farms might give biased results, because the assignment of farms into the groups is not random, in other words selection bias might affect the results of comparison.

Therefore, the basic objective of an unbiased comparison is to get rid of selection bias. The two most common methods of accounting for selection bias in social sciences are matching and Difference in Difference (D-i-D) methods. In this paper, we use propensity score matching (PSM) in order to account for selection bias [7; 8].

RESULTS

Parameter estimates of the Random parameter Model

Selected parameter estimates of the estimated translog production SF Model are presented in Table 2.

The results show that all of the first order coefficients are statistically significant and have the expected sign (positive), i.e. monotonicity criteria that is suggested by production theory is satisfied. We conducted several tests before choosing this model. First, we tested Translog

against Cobb-Douglas functional form using Likelihood ratio test. The test clearly rejected Cobb Douglas functional form.
Next, we compared, traditional Normal/Half-Normal SFA model (where the effect of heterogeneity is not accounted for), True random effect Model (where heterogeneity affect only the intercept) with RPM (where heterogeneity affect not only the intercept, but all of the input variables, i.e. it has an effect on marginal productivity of all of the inputs) based on Akaike Information Criteria (AIC). The test clearly showed that RPM fit better to this data. The statistically significant values of all of the scale parameters are also indicate that RPM fit well to these data, and it is important to consider the effect of heterogeneity not only on the intercept but on input variables, too. Moreover, results show that material input was the most influential in the production and labour was the least important. Interestingly, the estimate of technological change is negative. It is unexpected that technology would regress sharply in such a short time period. One possible explanation for this negative sign is that technological change measured in this way does not measure purely the changes in technology, it is combined measure of technical and environmental change that is the negative sign is might be a consequence of worsening weather condition. However, further research is needed to examine the effect of weather on the production, but this is out of the scope of this paper. Another interesting feature of the nature of technological change. According to these estimates the nature of technological change was land using and intermediate consumption saving.

Table 2: Parameter Estimates (selected)

	Coefficients	**Standard Error**	**z**	**Prob |z|>Z***	**95% confidence interval**	
Random parameters						
Constant	0.257***	0.009	29.020	0.000	0.239	0.274
Time	-0.012***	0.002	-5.340	0.000	-0.017	-0.008
Labour	0.073***	0.007	9.830	0.000	0.057	0.086
Land	0.471***	0.013	35.980	0.000	0.445	0.497
Capital	0.109***	0.005	20.040	0.000	0.099	0.120
Materials	0.371***	0.012	32.110	0.000	0.349	0.394
Non-random parameters						
Time*Time	0.007**	0.004	2.010	0.044	0.000	0.015
Time*Labour	-0.001	0.003	-0.270	0.784	-0.007	0.006
Time*Land	0.040***	0.006	6.980	0.000	0.029	0.052
Time*capital	0.001	0.002	0.240	0.808	-0.004	0.005
Time*Materials	-.032***	0.005	-6.200	0.000	-0.042	-0.022
Asymmetry and variance parameter						
Sigma	0.395***	0.004	94.890	0.000	0.387	0.404
Lambda	3.428***	0.182	18.800	0.000	3.071	3.786
Scale parameters for random variables						
Constant	-0.224***	0.004	-53.340	0.000	-0.233	-0.216
Time	0.014***	0.002	6.770	0.000	0.010	0.019
Labour	-0.030***	0.006	-5.460	0.000	-0.041	-0.019
Land	-0.058***	0.010	-5.770	0.000	-0.078	-0.039
Capital	0.011***	0.004	2.610	0.009	0.003	0.020

Materials	0.099***	0.008	12.100	0.000	0.083	0.115

Source: Own calculation based on FADN data

Drivers of technical efficiency

In order to examine drivers of technical efficiency we regressed TE on different exogenous drivers: Economic Size Unit (ESU), education (of farm manager), other income, soil quality, number of owners, irrigate, age (of farm manager) and organic. We used the variable irrigate as a dummy variable, it shows whether a farm has some irrigated land or not. Organic is also a dummy variable: 0 conventional farms; 1 organic farms. Results are shown in Table 3.

Table 3: Drivers of technical efficiency

	Coefficients	**Standard Error**	**z**	**Prob |z|>Z***	**95% confidence interval**	
Economic Size Unit	0.647D-04***	.201D-04	3.220	0.001	.252D-04	.104D-03
Education	0.002***	.435D-04	36.750	0.000	0.002	0.002
Other Income	0.221***	0.008	28.970	0.000	0.206	0.235
Soil Quality	0.005***	0.000	15.210	0.000	0.005	0.006
Nr. Of owners	-0.001***	0.000	-5.330	0.000	-0.001	-0.001
irrigate	0.074***	0.015	5.060	0.000	0.045	0.103
Age	0.001***	.365D-04	11.120	0.000	0.000	0.000
Organic	0.521D-04	.418D-04	1.250	0.213	-0.298D-04	.134D-03

Source: Own calculation based on FADN data
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
****, **, * ==> Significance at 1%, 5%, 10% level.*

Table 3 shows: the higher value of ESU, education, other income, soil quality, irrigation and age increase technical efficiency whereas the higher number of owners decrease. We included also the variable organic to test whether organic production affect technical efficiency or not. The result show that it does not has any significant effect on TE.

Comparison of TE and TFP

The mean comparison of estimated TE and TFP scores can be found in Table 4.

Table 4: Mean Comparison of TE and TFP

	Mean	**Standard Deviation**	**Minimum**	**Maximum**	**Observations**	**Prob > |z|**
	TE					
Conventional farms	1.01	0.13	0.48	1.34	2968	-
Organic farms	0.95	0.15	0.78	1.18	6	-
Mann-Whitney test	-					0.322
	TFP					
Conventional farms	0.76	0.13	0.12	0.96	2968	-
Organic farms	0.72	0.18	0.50	0.96	6	-
Mann-Whitney test	-					0.526

Source: Own calculation based on FADN data

Table 4 shows that both the TE and TFP of conventional farms are to some extent higher compared to organic farms. We tested whether these differences are statistically significant or not using Mann-Whitney test. The test shows that the differences are not significant. However, this comparison may be biased, therefore in the next section we apply matching method in order to correct for sample selection bias.

Comparison of TE and TFP using matching method

The decision of how many variables to include into the matching procedure is widely discussed in the literature. First, we checked main differences between organic and conventional farms in terms of standardised bias. We found that there is a big difference in economic size, educational level and soil quality between these groups of farms. Therefore, in our matching procedure we control for these variables. Educational level was measured in a scale from 1 to 5: 1 no lowest educational level, 5 the highest educational level. Soil quality is based on a Hungarian soil qualification system; the higher value means better quality.
We tested different matching algorithms and we choose thee one where the mean bias was the smallest after matching.
Figure 1 shows the mean bias matching for different matching algorithms and for different number of nearest neighbours. It shows that the mean bias is the lowest with 6 nearest neighbours, therefore we choose this type of matching for the comparison of farms' performance.

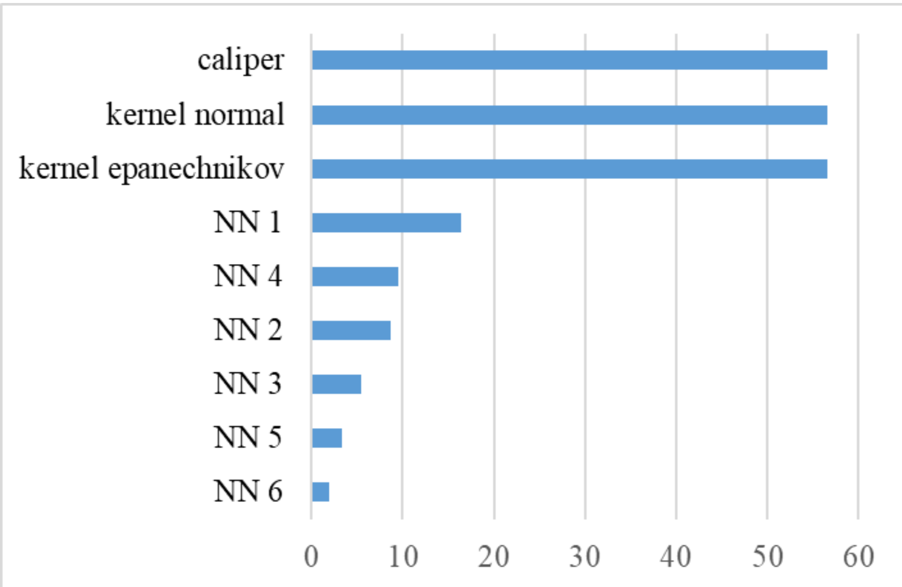

Figure 1: Mean bias after matching
Source: Own calculation based on FADN data

Table 5 shows that the applied matching algorithm, balanced well the sample; all the differences in the covariates that were statistically significant before matching disappeared after matching.

Table 5: Differences in the matched and unmatched sample

Variable	Unmatched(U)/ Matched(M)	Mean			% reduce bias
		Treated	Control	%bias	
ESU	U	73.5	141.7	-46.9	
	M	73.5	72.6	0.6	98.7

Soil quality	U	16.9	18.0	-12.7	
	M	16.9	17.3	-4.9	61.1
Education	U	1.0	2.1	-110.3	
	M	1.0	1.0	0.0	100.0

Source: Own calculation based on FADN data

The results of treatment effect analysis are reported in Table 6.

Table 6: Average Treatment effect on the Treated

	Coef.	**Robust Std. Err.**	**z**	**P>|z|**	**[95% Conf. Interval]**	
TE	-0.045	0.078	-0.580	0.564	-0.199	0.108
TFP	-0.061	0.075	-0.810	0.416	-0.209	0.086

Source: Own calculation based on FADN data

Results shows that the differences between organic and conventional farms in TE and TFP is not statistically significant.

CONCLUSIONS

The aim of this paper was to compare the TE and TFP of organic and conventional COP crop producing farms. We estimated TE using a random parameter stochastic production frontier. The model suited well to this dataset, most the variables were significant, and criteria suggested by economic theories were fulfilled. Based on the estimated parameters of the model we constructed a Törnquist-Theil TFP index. First, we compared the performance of the groups with standard statistical test. Results showed that both the TE and TFP of organic farms are smaller, but the difference were not statistically significant. Second, we compared TE and TFP based on propensity score matching in order to eliminate potential selection bias. After controlling for selection bias the difference remained insignificant.
One limitation is the low number of organic farms in our sample.
Another limitation of such kind of comparison is the lack of appropriate deflators. In order to estimate a production frontier using FADN data in most of the cases, one has to use implicit quantity indices for the output variable(s) and some of the input variable(s) (e.g. intermediate consumption). Organic farms usually can sell their products for higher prices and might buy some of their inputs for higher prices compared to conventional farms. In case the same price indices are used to deflate, the monetary variable(s) used in the production frontiers both for organic and conventional farms, the implicit quantities will be biased in the case of organic farms. With the more appropriate price indices, the more accurate performance analysis would be possible.

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REFERENCES

[1] CAVES, D. W., CHRISTENSEN, L. R., & DIEWERT, W. E. (1982). Multilateral comparisons of output, input, and productivity using superlative index numbers. *The economic journal*, *92*(365), 73-86. ISSN 00130133

[2] GIILLESPIE, J., & NEHRING, R. (2013). Comparing economic performance of organic and conventional US beef farms using matching samples. *Australian Journal of Agricultural and Resource Economics*, *57*(2), 178-192. ISSN 1467 8489 https://doi.org/10.1111/j.1467-8489.2012.00610.x

[3] GREENE, W. (2005). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of econometrics*, *126*(2), 269-303. ISSN: 0304-4076 https://doi.org/10.1016/j.jeconom.2004.05.003

[4] LAKNER, S., VON CRAMON-TAUBADEL, S., & BRÜMMER, B. (2012). Technical efficiency of organic pasture farming in Germany: The role of location economics and of specific knowledge. *Renewable Agriculture and Food Systems*, *27*(3), 228-241. ISSN: 1742-1705

[5] MAYEN, C. D., BALAGTAS, J. V., & ALEXANDER, C. E. (2010). Technology adoption and technical efficiency: organic and conventional dairy farms in the United States. *American Journal of Agricultural Economics*, *92*(1), 181-195. ISSN:1467-8276

[6] PESTI, Cs., KESZTHELYI, Sz., BARKASZI, L., KÁRPÁTI, A., SZECSŐ, M., KORONDINÉ DOBOLYI, E., KIS-CSATÁRI, E. (2010). A különböző típusú üzemek jövedelmét befolyásoló tényezők vizsgálata és nemzetközi összehasonlítása. Agrárgazdasági Információk. 2010. 2. sz. 1-66.HU ISSN 1418 2130

[7] ROSENBAUM, P. R., & RUBIN, D. B. (1983a). Assessing sensitivity to an unobserved binary covariate in an observational study with binary outcome. *Journal of the Royal Statistical Society: Series B (Methodological)*, *45*(2), 212-218. ISSN 0035 9238

[8] ROSENBAUM, P. R., & RUBIN, D. B. (1983b). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41-55. ISSN 0006 3444 https://doi.org/10.1093/biomet/70.1.41

[9] TSIONAS, E. G. (2002). Stochastic frontier models with random coefficients. *Journal of Applied Econometrics*, *17*(2), 127-147. ISSN:1099-1255 https://doi.org/10.1002/jae.637

[10] DJOKOTO, J. G., OWUSU, V., AWUNYO-VITOR, D. (2020): Is organic agriculture more scale efficient than conventional agriculture? The case of cocoa cultivation is Ghana. *Review of Agricultural and Applied Economics*, Vol. XXIII, Issue 2, 112-123. ISSN 1336-9261

[11] NEHRING, R. F., GILLESPIE, J., GREENE, C. and LAW, J. (2021): The Economics and Productivity of Organic versus Conventional U.S. Dairy Farms. *Journal of Agricultural and Applied Economics* (2021), 53, 134–152. ISSN 1074-0708 https://doi.org/10.1017/aae.2020.34