

AN ANALYSIS OF THE IMPACTS OF WEATHER ON TECHNICAL EFFICIENCY IN CZECH AGRICULTURE

Barbora Hřebíková¹, Lukáš Čechura¹

¹ Department of Economics, Faculty of Economics and Management, Czech University of Life Sciences Prague, Kamýcká 129, 165 21 Praha 6-Suchbát, Czech Republic

Abstract

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Although weather is a significant determinant of agricultural production, it is not a common practice when analysing production to control for its impact. The problem is methodological, since it is difficult to find a proper proxy variable for weather in these models. The aim of this study is to investigate these issues. First, several possibilities for describing weather and its inclusion into stochastic frontier models are defined and discussed. Then, the explicit impact of weather on the technical efficiency of Czech farmers in different regions of the Czech Republic for the period 2004–2009 is analyzed and discussed. We use a proxy variable in the form of Iowa indices in the production analysis, in order to capture the impact of weather on technical efficiency. A stochastic frontier production function model in the form of the BC Model is defined, and weather enters the model as a variable explaining technical inefficiency. The paper arose within the framework of solution of the 7th FP EU project COMPETE no 312029.

Keywords: technical efficiency, weather, SFA (Stochastic Frontier Analysis), Czech agriculture

INTRODUCTION

The biological properties of a particular farming commodity determine its need for specific climatic conditions, such as mean and extreme temperatures, precipitation amounts, hours of sunshine, etc. Our main aim is to go beyond empirical knowledge and find a model that will describe and quantify the impact of weather as part of a multi-factor influence on production, that is to say, one of many mutually (un)conditioned factors determining the final production. In recent decades, many studies have focused on the specification of how weather impacts production in relation to planting region. The result of such a direction in the theory is, that it has also been proven scientifically that weather has a strong influence on the output of plant production, and in fact a number of different projects and systems dealing with prognostics, forecasting, and modelling and simulation of agro-meteorological relations have been developed.

The specific goals of EU policy include, for example, the ENSEMBLES project, the CECILIA project and the PRUDENCE project, conducted by the EU, which was initiated in order to detect the weaknesses of climatic projections and would eliminate the uncertainty in forecasting the impacts of climatic change in Europe. The ENSEMBLES project, the MARS system, developed within the activities of JRC, which uses the Crop Growth Monitoring System to provide the European Commission with timely and quantitative yield forecasts at the regional and national levels (currently in use within one particular MARS action known as AGRI4CAST), the Intergovernmental Panel on Climate Change (IPCC), and the European Commission's project study ClimSoil, which was aimed at providing an understanding of interactions between soil under different methods of land use and climate change, and was linked to EC performance of the Thematic Strategy on the protection of soil for the Soil Framework Directive, etc.

In general, the main objective is to describe with the highest probability the influence of weather conditions on crop production and vice versa. Apart from well-developed agro-meteorological systems (whose purposes and focus differ significantly from systems that are to be used within economics), econometrics-based approaches mainly attempt to combine production models with meteorological models, and they simply include the described weather impacts into the deterministic part of the production function. However, there is increasing focus on the use of a relatively recently founded approach which examines the stochastic production frontier and the technical efficiency of producing. Nevertheless, there is still a considerable lack of studies that include weather in production frontier analyses, in a different way than just as a part of statistical noise. The main reason for this could be found in methodology, as it is generally difficult to find a proper proxy variable for weather to enter into specific models.

The aim of this paper is to define and discuss several possibilities for describing weather and its influence on the level of technical efficiency. We use stochastic frontier analysis to estimate these effects. The study computes Iowa indices (denoted as K_{it}) and uses them as a proxy variable to capture the impacts of weather on technical efficiency. This climatic index is based on the assumption that deviations from the long-term trend result from the impacts of weather on production. With the given inputs and technology of growing, output would thus reach the values forecast by means of the trend function. Differences between these values and the real output values are therefore the results of uncertain and unpredictable conditions, such as the weather. The methodology of the Iowa indices and its alternation was used in a corresponding research problem by the Danish State Institute of Agricultural and Fisheries Economics in the Regional Econometric Sector Model for Danish Agriculture (ESMERALDA), among others.

Weather can basically enter the models in two different ways. In the previous study, specific weather features (average monthly temperature and total monthly precipitation) were treated as simple production factors – independent variables (see e.g. Hedy, 1965) – and the results were seen as a benchmark for further analysis. Here, weather in the form of K_{it} is treated as a variable, which explains technical inefficiency (weather is included in the distribution of one-sided error term). We assume that such an inclusion of weather into the models leads to better specification.

The paper is structured as follows: the next section introduces the dataset and methodology; the third section presents empirical results; and

the final section provides discussion and concluding remarks.

MATERIALS AND METHODS

Data

All frontier models are estimated using an unbalanced panel dataset that covers the period 2004–2009. Estimation is based on a sample consisting of 1,248 individuals. The dataset consists of three sets of data.

Data on yields in the given 14 regions of the Czech Republic was drawn from public databases of the Czech Statistical Office (CSO). It contains information on the production of crops (wheat and barley), potatoes, sugar beets and rapeseed in the years 1994–2009.

Data concerning individual production was drawn from the Albertina database, collected by Bisnode Česká republika, a.s. Specifically, we use information from the final accounts of companies whose main activity is agriculture, namely plant and mixed production, according to the NACE classification. Therefore the analysis concerns agricultural companies, i.e., corporations.

Finally, the database LPIS was used as a source for the input factor land.

The variables entering the models are specified as follows: output (y), labour (A), land (L), capital (K), material inputs (V), climatic index (K_{it}). Output is represented by total sales of a company's own products and services and was deflated by the index of agricultural prices (2005 = 100). The labour input is total personnel costs per company, divided by the annual regional wage in agriculture (region = NUTS3). The land variable is corrected by the land quality. The correction was made using information about the official price of land. Capital is represented by the book value of tangible assets and is deflated by the index of processing (industry) prices (2005 = 100). Finally, the material inputs are used in the form of total costs of material and energy consumption per company and are deflated by the index of processing prices (2005 = 100).¹

Calculation of the Climatic Index in the Form of K_{it}

Particular climatological characteristics (such as monthly mean temperature, total monthly precipitation, etc.) are features, which can be used for a direct modelling of a weather impacts in a variety of relationships in a wide range of areas. Weather conditions can also be specified, with regard to the purposes of the use for these specifications, in the form of various dummy variables. If these variables are correctly specified, they can sometimes

1 The source of prices for deflation is the Czech Statistical Office.

be more appropriate in numerous problems than if a direct description of weather features was used.

Due to the methodology of its calculation, a climatic index in the form of an Iowa index is a good tool for measuring weather impacts on TE, since it relates directly to production output, namely the crop yield. It is based on trend functions.

We assume that fitted yield trends have a positive trend since the technology and growing conditions are improving constantly. Furthermore, we assume that the trend could change within the whole period of 1994–2009 due to the ongoing transition process and the obtained membership in the EU, which carries the burden of fulfilling CAP. This assumption is controlled by using the time series beginning at a different point within the given period of 1994–2009. For each region, and every commodity grown in that particular region, trend functions of polynomial (quadratic and cubic), square root, exponential, logarithmic, and fractional rational function types were fitted and further verified by the criteria of maximum R-squared (R^2) and minimal deviation of ex-post forecasted values from the last 4 observations in the time series (representing the period for which the Czech Republic has been a member of the EU).

We found that the fitted trends were more accurate using data from much later than 1994. Finally, we used the time series beginning with the year 2004, because most trend functions had reached a stable correspondence with real values, compared to the trend functions fitted for other periods of time. In addition, there were significant changes in growing methods and technologies for some of the commodities. In general, the most accurate function for describing the trends in yield output happened to be a cubic function exhibiting degressively-progressive behaviour.

A function corresponding to the yield development was thus derived for every single commodity in each region. This trend function was further used to compute the climatic index (K_{it}) (so-called Iowa index):

$$K_{it} = \frac{\sum_j k_{jit} \times g_{jit}}{\sum_j g_{jit}},$$

where i represents the i -th region, j stands for the j -th crop, t refers to time effects and represents the t -th year of the studied period, g_{jit} is the weight of a certain crop in the region in proportion to the output at time t , y_{jit} represents the yield of a certain crop in a certain region at time t , and k_{jit} stands for a ratio of the observed and ex-post forecasted values $y_{jit}/\hat{y}_{jit}$.

The advantages of the inclusion of climatic index into the distribution of the one-sided error term is the fact that there is no need to collect data on specific weather conditions. Although such an approach might seem quite simplistic, it is sometimes much more precise tool for identifying the impacts of weather than slightly more sophisticated models

which include weather variables in production determinants (see e.g. Hřebíková, 2008). In a similar fashion, a respective alternation of Iowa indices were used in, for example, the Regional Econometric Sector Model for Danish Agriculture (ESMERALDA), developed within an initiative of the Institute of Danish Agriculture and Fisheries, wherein it is stated that the „climate index can be calculated as the ratio between observed and standardised yield levels.“ (A documentation of the regionalized ESMERALDA model 47).

To decide on the weight used in the K_{it} formula, the portfolio of commodities in each region had to be considered. We could thereby see the importance of a given commodity in region i at time t regarding the region's portfolio. Therefore, the ratio of the yield (in t/ha) of commodity j in region i at time t and the sum of the yields (in t/ha) of all commodities in region i at time t will be multiplied by the ratio of the acreage of commodity j at time t in region i and the total acreage area of region i at time t covering all commodities.

Climatic indices are computed for each region at time t . Statistica software was used for the computation of climatic indices. The indices K_{it} are then assigned to every farm in the dataset, in relation to the farm's location. SFA is carried out using the LIMDEP software.

Transformed Value of Land – Standardisation of the Variable Land

Since our sample includes individuals from different regions of the Czech Republic, in order to capture soil quality differences in these regions we used the official price of land in the following way:

$$LAND_{Uit} = LAND_{it} \times UC_{Niu},$$

where $LAND_{Uit}$ is the quality-corrected LAND of a given individual i at time t , $LAND_{it}$ represents the quantity of the production factor land of a given individual i at time t , and UC_{Niu} is an index of the official price of a given region, relative to the price of the best region, i.e.:

$$UC_{Niu} = \frac{UC_i}{7.37},$$

where UC_i stands for the index of the official price of a given region and 7.37 is the numerical value of the price of the best region.

SFA

The empirical analysis is based on a model introduced by Battese and Coelli (1992 and 1995). Moreover, we assume that the transformation process can be well approximated by a translog production function. Our decision is based on the fact that the translog function is a flexible functional form.

The Battese and Coelli (BC) model is a modification of the REM model. Unlike REM,

the BC model allows the technical inefficiency term being time variant. The default form of the BC model is:

$$y_{it} = x'_{it}\beta + v_{it} - u_{it}$$

with

$$u_{it} = g(z_{it})|U_i|$$

and

$$g(z_{it}) = \exp[-\eta(t - T)], \text{ then}$$

$$u_{it} = \eta_i u_i = \{\exp[-\eta(t - T)]\} u_i$$

or

$$g(z_{it}) = \exp(\eta' z_{it})$$

where u_{it} is the inefficiency of individual i at time t , u_i is the inefficiency of individual i , η_i is an Eta parameter for the one-sided time variance of u_i , and T is the number of periods in the panel. z_{it} is a vector of exogenous variables. The function $\exp[-\eta(t - T)] = \eta_i$ represents a time-decay model with a half-normal or truncated distribution of inefficiency and preserves the time-varying aspect of u_{it} (LIMDEP version 9.0, pp. E33–54), and the function $\exp(\eta' z_{it})$ represents a model with heteroscedastic u_{it} , which can also be formulated in a truncated version.

Moreover, the model can be used for the estimation of heterogeneity among individuals, where the real variables that are associated with individual heterogeneity are included in the inefficiency effects, instead of proxy variables (Batesse, Coelli, 1995):

$$u_{it} = z'_{it}\delta + w_{it}$$

where $z'_{it}\delta$ is a vector of exogenous variables multiplied by a vector of unknown parameters (to be estimated), and w_{it} counts for the second part of the inefficiency effects. w_{it} is defined by a truncation of the normal distribution and u_{it} is a non-negative truncation of $N(z'_{it}\delta, \sigma^2)$ distribution (Batesse, Coelli, 1995). In this form, the model should theoretically reach lower average values of inefficiency term than in REM; in other words, scores of TE should be, on average, higher than the TE resulting from REM estimates.

RESULTS

The results provide an estimate of four different versions of the BC model. First, the model omitting any possible weather impacts (K_{it}) was estimated. Then, K_{it} was included in the mean of TE and the truncated version was obtained and estimated (model BC 2). The role of K_{it} in relation to the variance of TE was analyzed by estimating the BC model that controls for heteroscedasticity, where K_{it} entered first the variance of TE (model BC 3) and then both the mean and variance of TE (model BC 4).

Parameter Estimate

Tab. I provides parameter estimates of all four versions of the BC model (Note: ***, **, * in Tab. I refer to significance at the 1%, 5% and 10% level, respectively). All estimated models show that each of the production factors meets the conditions of monotonicity and quasiconcavity, except for the quasiconcavity condition in the case of the production factor land. Moreover, the significance of land varies in the fitted models. It ranges from a significance of $\alpha = 0.1$ in the model which does not control for weather impacts, BC1, and the model that includes weather impacts in both the mean and variance of u , BC4, to a significance of $\alpha = 0.05$ for the case in which weather enters the variance of u . Land has no statistical significance for the truncated version of the model, specified by BC2. As suggested by Čechura (2009), subsidies could have a counterproductive effect on the use of land, a fact that shall be an object of deeper analysis (Čechura, 2009). The estimates of other variables remain significant even with a 1% significance level.

The LR test does not reject the translog functional form for all model specifications (LR for BC1 = 2695.304, LR for BC2 = 2699.180, LR for BC3 = 2621.565, and LR for BC4 = 2630.249. See Tab. III). Since all variables are normalised in logarithm by their sample mean, the estimated first order parameters of inputs represent production elasticities. Thus, material (V) shows the strongest influence on the level of output in all models – a rise in the use of material by one percent increases the output by 0.63077 (BC1), 0.63069 (BC2), 0.62543 (BC3) and 0.62582 (BC4) percent. The second strongest factor is labour (A), followed by capital (K). Land displays the smallest influence on the level of final output. This is probably due to the fact that land is the least flexible factor in relation to production technology and its alternation. Inclusion of K_{it} into the mean of TE does not affect the level of influence of land upon output, but inclusion of K_{it} into the variance of TE results in land having a greater influence on the final output. This finding points to the possible mutual influence of land and weather and confirms our assumption that the inclusion of weather is adequate for a description of the analysed production frontier.

The sum of elasticities indicates that farms in the sample reach, on average, slightly decreasing returns to scale (BC1: $0.97702 < 1$, BC2: $0.9709 < 1$, BC3: $0.98444 < 1$, BC4: $0.97646 < 1$).

Technical change is statistically significant only for model specifications BC3 and BC4. It has a slightly negative effect on the level of output, with the value of $\beta_T = -0.02999$ for BC3 and $\beta_T = -0.03029$ for BC4, and its impact accelerates over time ($\beta_{TT} = -0.05511$ or $\beta_{TT} = -0.05568$). Biased technological change is pronounced and is labour-saving and material-using.

In all four models, the parameter lambda indicates that the variation in inefficiency is more pronounced

I: Parameter estimates BC models

model	BC1			BC2			BC3			BC4		
variable	parameter estimate	Std. Error	P(z > Z)	parameter estimate	Std. Error	P(z > Z)	parameter estimate	Std. Error	P(z > Z)	parameter estimate	Std. Error	P(z > Z)
Constant	0.33664***	0.01489	22.61	0.33558***	0.01499	22.39	0.39915***	0.01455	27.43	0.39495***	0.01451	27.21
T	-0.00548	0.00505	-1.08	-0.00629	0.00507	-1.24	-0.02999***	0.00476	-6.30	-0.3029***	0.00477	-6.35
TT	-0.04095***	0.00425	-9.62	-0.0418***	0.00431	-9.70	-0.0511***	0.00425	-12.97	-0.05568***	0.00426	-13.08
A	0.21540***	0.00977	22.04	0.21590***	0.00969	22.28	0.22377***	0.00961	23.29	0.22407***	0.00945	23.72
L	0.03696*	0.02022	1.83	0.03144	0.01991	1.58	0.04034**	0.02038	1.98	0.03323*	0.01992	1.67
K	0.09389***	0.00603	15.58	0.09287***	0.00597	15.56	0.09490***	0.00597	15.89	0.09334***	0.00589	15.85
V	0.63077***	0.01139	55.40	0.63069***	0.01135	55.58	0.62543***	0.01106	56.57	0.62582***	0.01092	57.29
AA	0.06867***	0.00331	20.75	0.06881***	0.00331	20.81	0.06858***	0.00333	20.59	0.06883***	0.00331	20.76
LL	0.09662	0.06052	1.60	0.09584	0.06058	1.58	0.0929	0.05857	1.59	0.09241	0.05870	1.57
KK	0.04447***	0.00351	12.68	0.04432***	0.00347	12.76	0.04940***	0.00349	14.16	0.04904***	0.00344	14.26
VV	0.12431***	0.00800	15.54	0.12392***	0.00797	15.55	0.11274***	0.00807	13.98	0.11240***	0.00803	14.00
AT	-0.01436***	0.00292	-4.93	-0.01438***	0.00292	-4.93	-0.01609***	0.00285	-5.64	-0.0161***	0.00286	-5.64
LT	-0.00719	0.00726	-0.99	-0.0076	0.00732	-1.04	-0.00298	0.00713	-0.42	-0.00324	0.00716	-0.45
KT	0.00603***	0.00228	2.64	0.00601***	0.00228	2.64	0.00302	0.00214	1.41	0.00312	0.00214	1.46
VT	0.00454	0.00299	1.52	0.00459	0.00299	1.54	0.01232***	0.00255	4.83	0.01225***	0.00257	4.76
AL	-0.06076***	0.01265	-4.80	-0.05993***	0.01264	-4.74	-0.06329***	0.01270	-4.98	-0.06225***	0.01265	-4.92
AK	0.00075	0.00512	0.15	0.00033	0.00517	0.06	0.00083	0.00515	0.16	0.00009	0.00516	0.02
AV	-0.08421***	0.00399	-21.11	-0.08373***	0.00399	-20.97	-0.07532***	0.00401	-18.76	-0.07482***	0.00403	-18.57
LK	0.13393***	0.01280	10.46	0.13182***	0.01273	10.36	0.13828***	0.01285	10.76	0.13501***	0.01274	10.60
LV	0.00941	0.01995	0.47	0.00800	0.01998	0.40	0.00826	0.01970	0.42	0.00631	0.01969	0.32
KV	-0.0294***	0.00473	-6.22	-0.02912***	0.00478	-6.09	-0.03518***	0.00470	-7.49	-0.03452***	0.00467	-7.39
Offset [mean = mu(i)] parameters in one sided error												
Constant												
LKIJT				-1.28013**	0.62289	-2.06				-1.77512***	0.5416	-3.28
Coefficients in u(i,t) = [exp(eta*z(i,t))* u(i)]												
Eta				-14.36	0.00463	-13.14						
LKIJT				-0.06079***	0.00463	-13.14				0.34289***	0.08431	4.07
Variance parameters for compound error												
Lambda	2.96321***	0.00417	711.41	2.98861***	0.00419	713.51	2.73269***	0.00389	702.65	2.76753***	0.00403	687.35
Sigma(u)	0.50720***	0.00190	267.54	0.51193***	0.00198	258.82	0.47105***	0.00125	377.99	0.47763***	0.00136	351.08
Log Likelihood function	302.167			304.104			265.297			269.639		
Sigma	0.53530			0.53983			0.50160			0.50785		
Sigma(v)	0.17116			0.17129			0.17238			0.17258		

Source: own calculations, Limdep

than the variation in the statistical noise. The values are between $\lambda = 2.73269$ and $\lambda = 2.98861$. Estimates without inclusion of K_{it} into the model, or into the variance of u , reach slightly higher values of lambda than estimates of models which include K_{it} into the variance of u . This corresponds with the theoretical assumption that the inclusion of variables which represent the impact of the weather explains part of the inefficiency. In this case it decreases the variance of u . We have therefore explained part of the inefficiency term that is related to the impact of weather on agricultural production. A comparison of characteristics describing the estimated TE in all BC models is provided in Tab. II. (Note: ***, **, * in Tab. II refer to significance at the 1%, 5% and 10% levels, respectively).

Specifically, regarding K_{it} and its impact on TE, when it is included into the mean of TE (model BC2), it shifts farms closer to the frontier. In other words, it lowers the inefficiency compared to the model that does not control for weather impacts at all (specification BC1). The BC specification allows for the time variance of inefficiency effects. The parameter $\eta = \eta$, which describes the time variance of u , is -0.06079 for the case when K_{it} is included in the TE mean, and it is significant at a level of $\alpha = 0.01$, confirming that technical efficiency varies over time. The third model specification, BC3, reveals the variance in the one-sided error term being significantly influenced by K_{it} (it reduces the variance of u). Omitting weather impacts from the specification of technical efficiency could overvalue the inefficiency effects. Therefore, in order to have a complete picture of weather impacts on technical efficiency, a stochastic production frontier model which includes K_{it} in both the mean of TE and the variance of TE was estimated. The influence of K_{it} is significant in relation to both the mean and the variance in technical efficiency at a 1% significance level. Such inclusion of the weather variable lowers the mean of inefficiency term and thus shifts the average

technical efficiency of the sample to 0.744635, meaning that the average technical efficiency reaches 74.5%. The average of TE estimated in BC1 is 73.8%. Moreover, the inclusion of K_{it} in model BC4 explains the variance of technical inefficiency term. The significance of K_{it} in the variance of u confirms its role in the distribution of u , i.e. in this case it reduces the variance of u . Moreover, the significance of K_{it} in mean of u confirms individual heterogeneity effect. Model BC3 does not account for the heterogeneity of the sample, although it does describe the influence of K_{it} on the variance u . The mean of u is 0.740467 in the case of BC3, meaning that the average technical efficiency reaches around 74%.

DISCUSSION

The results are in line with our assumption that the inclusion of weather impacts into the specification of technical efficiency leads to a better model specification, resulting in a higher quality technical efficiency estimate.

There is a theoretical assumption, resulting from the algorithm of the BC estimate, that the inclusion of variables relating to individual heterogeneity should logically lead to a lower technical inefficiency. Thus, the higher mean value of TE confirms this assumption. Comparing each of the two corresponding specifications of the model, one with no K_{it} included in the mean of u and one with K_{it} specified in the inefficiency mean, clearly shows that the mean value of TE is higher in the case of the truncated version ($BC1 = 0.737873 < BC2 = 0.740682$, and $BC3 = 0.740467 < BC = 0.744635$).

As we mentioned in the introduction, the authors generally adopt approaches where, due to vague methodological options for controlling weather impacts on production, they either simply include weather impacts described by expert meteorological models into the deterministic part of the production function or they leave weather as a part of statistical

II: Descriptive statistics of technical efficiency

Characteristic Model	Lambda	Standard deviation Lambda	Variance of u σ_u	Standard deviation of σ_u	Standard deviation of TE	Mean of TE
BC1	2.96321***	0.00417	0.50720***	0.00190	0.141466	0.737873
BC2	2.98861***	0.00463	0.51193***	0.00198	0.141887	0.740682
BC3	2.73269***	0.00389	0.47105***	0.00125	0.140672	0.740467
BC4	2.76753***	0.00403	0.47763***	0.00136	0.141228	0.744635

Source: LimDep and own calculations

III: Comparison of distributional and explanatory properties of BC models

Model	Log Likelihood	LogLikelihood for $\sigma(u) = 0$	MLE – Chi squared (1)	AIC	LR
BC1	302.166	-1045.486	5379.97	-556.3(-0.118)	2695.304
BC2	304.104	-1045.486	5379.97	-558.2(-0.118)	2699.180
BC3	265.297	-1045.486	5379.97	-482.6(-0.102)	2621.565
BC4	269.639	-1045.486	5379.97	-489.3(-0.104)	2630.249

Source: Limdep and own calculations

noise. The latter corresponds to our specification BC1. This specification shows the lowest TE score, presumably due to the insufficient specification of technical inefficiency term. This conclusion confirms our assumption that the inclusion of weather into models, in the form of a proper proxy variable which explains technical inefficiency, leads to the better model specification. This way the paper contributes to other studies on efficiency of Czech agriculture (e.g. Curtiss, 2002; Špička, 2014; Čechura, 2012, 2014 and Čechura *et al.*, 2015).

Estimated parameters that pick up time variance are significant in all estimates. By comparing the results of BC with the results of other SFA models which do not account for the time variance of TE, the time variance of TE can also be justified. Thus, as a next step in the analysis, the estimation of Random parameter model (Tsionas, 2002) or Fixed effects model (Greene, 2004) is recommended. That gives the possibility of verifying learning-by-doing behaviour, which firms are assumed to adopt over time.

The BC model provides sufficient and satisfactory results for our analysis, and it confirms that inclusion of weather impacts into the specification of TE is reasonable and leads to a production frontier model with better statistical features.

Concerning the Iowa index, it happens to be a tool that is sufficient for representing weather impacts on production output when stochastic frontier analysis – particularly the BC specification

of a model – is used. However, we believe that other specifications could be found which would give the analyzed weather impacts a more concrete character (for example, using real climatic data, such as mean monthly temperatures or monthly totals of precipitation).

Following Čechura (2009), we expect that problems with the significance of land in all the cases discussed above have a logical explanation in the effect of subsidizing, and that they can be improved by inclusion of this effect into the model. Bakucs, Ferto and Fogarasi (2008) present the same conclusion in their study of the technical efficiency of Hungarian farms before and after accession. They conclude that public subsidies prevent farmers from being efficient. Moreover, we assume that better specification of soil quality for the production factor land and implementation of the quality of managerial competence could possibly yield even better statistical results. This assumption is based on studies made by Bokusheva and Khumbakar (2008), who included farm size and managerial competence into TE determinants, and by Hockmann and Pienadz (2007), who included human capital, which they assumed to be representative of managerial skills, into variables affecting TE levels, and it is also based on a conclusion made in the EC study report ClimSoil (2008), where it is claimed that “Climate change affects the soil carbon pool and vice versa ... for these relationships, land use and land management are major factors” (ClimSoil 26).

CONCLUSION

Considering the impacts of the weather, estimates of the Battese-Coelli model display a more precise and realistic estimate of technical efficiency. In other words, the weather explains part of the inefficiency if it is included in the stochastic frontier model.

When included in the mean of TE (model BC2), K_{it} shifts farms closer to the frontier because it lowers the value of inefficiency compared to the model that does not control for weather impacts at all (specification BC1). Furthermore, the third model specification, BC3, reveals the variance in the one-sided error term to be significantly influenced by K_{it} . This fact indicates heteroscedasticity of the sample and, together with the results of the first BC model, implies that omitting weather impacts from the technical efficiency specification overvalues inefficiency effects because the heteroscedasticity that is present is disregarded. In order to have a complete picture of the impact of weather on the technical efficiency of our stochastic production frontier, a model which includes K_{it} in both the mean and the variance of TE was estimated (BC4). In this specification, the influence of K_{it} is significant in relation to both the mean and the variance of technical efficiency. The importance of the influence of weather is higher than in the model which does not control for heteroscedasticity (BC2). The BC4 model suggests both significant heterogeneity and heteroscedasticity in the sample. The Iowa index that is used in this analysis seems to be an appropriate proxy, representing weather impacts on production output. The analysis clearly confirms that the inclusion of weather impacts into the specification of technical efficiency is reasonable, and leads to a better model specification with a better and more precise estimation of technical efficiency.

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Contact information

Barbora Hřebíková: bhrebikova@pef.czu.cz
 Lukas Čechura: cechura@pef.czu.cz