Technical efficiency and productivity change in German large-scale arable farming

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Abstract

This paper provides an assessment of technical efficiency and productivity change for a sample of large-scale arable farms in Germany. For this, the paper applies input-oriented Data Envelopment Analysis (DEA) and Malmquist Index (MI) methods in combination with bootstrapping to a balanced five-year panel data set of 86 German large-scale arable farms over a time period from 2012/2013 to 2016/2017. The DEA results of the original sample show a mean input-saving potential of 9.2 % across farms and time periods. The bootstrapped confidence intervals indicate no statistically significant difference among the mean scores for individual years, however significant differences exist between individual farms. The results of the MI analysis of the original sample suggest a mean annual growth in total factor productivity of 5.4 %. This progress was driven by technical change (6.5 %) and happened despite a small average deterioration in change in technical efficiency (1.1 %). The progress in total factor productivity as well as technical change is statistically underpinned through the bootstrapped confidence intervals. The result of change in technical efficiency computed from the original sample cannot be confirmed statistically as the corresponding confidence interval includes unity.

Keywords

Efficiency, productivity, DEA, Malmquist, bootstrapping, arable farming

1 Introduction

The world is facing the challenge of feeding approximately nine billion people by the middle of the century (GODFRAY et al., 2010). In order to meet the rising demand for food, global agricultural production needs to be increased by at least 60 % between 2012 and 2050 (ALEXANDRATOS and BRUINSMA, 2012). Human population increase, urbanization, a rise in per capita incomes and a westernization of diets in transformation countries are the key drivers of the growing food demand (GRAFTON et al., 2015). Since certain production factors such as land or water are limited, growth in agricultural productivity and a more efficient way of utilizing limited inputs are necessary if the agricultural sector's output is to keep up with the increasing demand for food and raw materials (ALEXANDRATOS and BRUINSMA, 2012; COELLI and RAO, 2005). Productivity increases have also become more important from an individual farm enterprise point of view, as rising production costs as well as domestic competition for limited factors such as land have enhanced the value of productivity growth and technical efficiency (BALMANN and SCHAFT, 2008).

In the context of assessing technical efficiency the nonparametric Data Envelopment Analysis (DEA) approach constructs an efficient frontier consisting of the best observations of the sample at a certain time. Malmquist indices (MI), which also use the DEA approach in their calculation, display growth in total factor productivity (TFP), which can be further decomposed into changes in technical efficiency and changes in technology (BALCOMBE et al., 2008a; FÄRE et al., 1994). Obtaining efficiency scores and consideration of productivity growth and its components over time can contribute towards a more economical factor input use and a more efficient production program (OUDE LANSINK et al., 2002). Over the past 20 years a broad variety of studies have been carried out in many different countries using DEA and MI approaches comparing individual farm data. The DEA methodology has proven very popular among productivity researchers, as it has the advantage that benchmark enterprises can be identified in the case of non-monetary input and output variables. However, there is one major disadvantage to the DEA procedure, which might lead to ambiguous results. As the DEA does not provide any information regarding the estimates' uncertainty, an assessment of whether differences between estimates are statistically significant is not possible (ODECK, 2009). As a solution to this limitation SIMAR and WILSON (1998, 1999) proposed an approach of applying EFRON's (1992) bootstrapping method to the results of the DEA and MI analysis. Their approach results in the calculation of boot-

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strap confidence intervals, which allow an interpretation regarding statistical inference and significance and therefore more robust conclusions (ODECK, 2009). This remedy to one of DEA's severest limitations, however, has not been used in many studies regarding agriculture. Even fewer studies apply this approach on an individual farm enterprise level in combination with MI calculations from a panel data set. So far, a study on 19 Eastern Norwegian grain farms over ten years by ODECK (2009) is the only paper combining the calculation of technical efficiency scores via DEA and productivity growth through MI with bootstrapping as suggested by SIMAR and WILSON (1998, 1999). Empirical research on technical efficiency and productivity change for German arable farms - especially using DEA and MI - has not been conducted in a long time.

This paper applies DEA and MI methods as well as bootstrapping of those results to a five-year balanced panel data set of 86 large-scale arable farms in Germany over a time period from 2012/2013 to 2016/2017. Against the background of the increasing size of arable farms in the course of advancing structural change, the consideration of large-scale farms seems to make sense, as they represent the future of the sector. The aim of this research is twofold. Firstly, this paper seeks to determine the degree of technical efficiency in German large-scale arable farming. Secondly, it aims to evaluate the magnitude of productivity change in German large-scale arable farming and whether it is mainly due to changes in technical efficiency or changes in technology for a time period that has not been evaluated so far. In this context it aims to provide statistical evidence regarding efficiency and productivity measurements for German arable farms and to illustrate the bootstrapping procedure of DEA and MI results in an agricultural application.

To the best of our knowledge there are multiple factors differentiating this study from previous ones. It is the first study combining DEA, MI and bootstrapping of both methods on an individual farm level data set for German agriculture. A micro-level analysis offers the most in-depth understanding of a sector (MARZEC and PISULEWSKI, 2019). The balanced panel data set of 86 farms over five years is the largest assessed on the individual farm level using the bootstrapping approach for DEA and MI combined. Therefore, this study's results are more reliable than previous studies as the nonparametric DEA performs better the more observations are included (BANKER et al., 1984). The larger sample size, the timeliness of the assessed time period from 2012/2013 to 2016/2017 as well as the regional focus on Germany - the European Union's second largest crop producer - differentiates the study from ODECK (2009). Additionally, more production inputs are embedded in the theoretical model which enables a more precise description of the production process. Lastly, most other studies on technical efficiency evaluate shorter periods of time. The results of studies on technical efficiency and productivity growth are particularly of interest to policy makers since these factors play a vital role in the planning of structural transformation processes and agricultural subsidy programs and reforms as well as in comparisons of the level of economic development between countries and regions (FRANCKSEN and LATACZ-LOHMANN, 2006; LISSITSA and ODENING, 2001). Furthermore, the European Union aims to reduce resource inputs within the food chain by 20 % by the year 2020 (European Commission, 2011) and has declared an increase in efficiency and productivity in the agricultural production as a priority (European Union, 2013; ŠPIČKA, 2015).

The remainder of this paper is structured as follows: Section 2 provides an overview of the existing research on efficiency and productivity change with bootstrapping on the individual farm level as well as a brief summary of previous findings regarding efficiency and productivity in the German agricultural sector. Subsequently section 3 briefly explains the applied methodology of DEA, MI and bootstrapping before the assessed data set is described in section 4. The results of this study are presented and discussed in section 5 and section 6 offers some concluding remarks.

2 Definition of terms and literature review

This section first explains the terms of technical efficiency and productivity change with their respective methods of evaluation. Afterwards a brief overview of the existing literature regarding DEA, MI and bootstrapping as well as findings on technical efficiency and productivity growth in German agriculture is provided.

Technical efficiency in the context of this paper's methodology is based on FARRELL (1957). The concept of Farrell's measure is to look at proportional changes - the same percentage decrease in all inputs or the same percentage increase in all outputs. Therefore, the Farrell input efficiency measures how much the input can be reduced without affecting the output. It's the most common approach of measuring the efficiency in a multi-input multi-output setting (BOGETOFT and OTTO, 2011). Efficiency can be estimated using parametric or nonparametric measures. When using a parametric estimation measure a stochastic production frontier or a stochastic cost frontier has to be specified. This Stochastic Frontier Analysis (SFA) allows for hypothesis testing, as it includes a stochastic error. However, the main disadvantage of this procedure is the fact that an explicit functional form and distribution have to be assumed. The nonparametric DEA introduced by CHARNES et al. (1978) has the advantage of no parametric restrictions on the observed technology reducing the potential of model misspecification. The major disadvantage of DEA is the susceptibility to measurement errors and data noise (HOANG LINH, 2012). Generally, DEA approaches are considered more suitable opposed to other efficiency measures if there is a certain degree of uncertainty regarding the data generating process (DGP), if price data is not available or if the existing price data cannot sufficiently express economic scarcity (BOGETOFT and OTTO, 2011; MUSSHOFF et al., 2009).

SOLOW (1956) was the first to assign the unexplained increase in output to technological change and therefore shaped the term of TFP in 1956. TFP is the amount of output, which the input factors used in production do not account for. TFP is determined by the efficiency and intensity with which the input factors are utilized (COMIN, 2010). The growth rate of TFP is usually interpreted as a measure of technical change (BRÜMMER et al., 2002). The first researchers to attempt a decomposition of TFP growth in individual components were NISHIMIZU and PAGE (1982) followed by BAUER (1990), who used a parametric approach, which required exact functions for technology. In 1994 FÄRE et al. introduced the first nonparametric decomposition approach. By calculating the geometric mean of two-DEA estimated MI they decomposed TFP growth into changes in technical efficiency and changes in technology over time. This method constructs a best practice frontier based on the data included in the sample and compares each Decision Making Unit (DMU) to said frontier. If a DMU gets closer to the frontier (catching-up) it's considered a growth in efficiency, if the frontier shifts with regard to a DMU's input mix (innovation) it is considered a technological change (FÄRE et al., 1994). A more extensive description of this approach is given in the methodology section.

This approach has been widely used to obtain a more exact assessment of TFP growth and its components. Many early research papers focus on comparing agricultural sectors of different countries (BUREAU et al., 1995; FUGLIE, 2010; FULGINITI and PERRIN, 1997; NKAMLEU, 2004; SUHARIYANTO and THIRTLE, 2001). But there has also been a broad range of DEA and MI research without bootstrapping on the individual farm level. OUDE LANSINK et al. (2002) for instance compared efficiency and productivity growth of conventional and organic farms from Finland over a three-year period. THIELE and BRODERSEN (1999) compared the efficiency of West and East German farms over a time period from 1995 to 1997. They showed that West German crop farms were more productive than East German crop farms with an average input reduction potential of 17 % and 22 %, respectively. ZAWALINSKA (2004) and LATRUFFE (2004) both evaluated individual farm data from Poland over the time period from 1996 to 2000. Their assessments showed a decline in productivity and inconsistent results regarding the technical efficiency. Other examples are provided by GOCHT and BALCOMBE (2006) for Slovenian wheat farms or by COELLI et al. (2006) for Belgian mixed farms.

Table 1 provides an overview of recent studies using DEA or MI in combination with bootstrapping as suggested by SIMAR and WILSON (1998, 1999). It is notable that only the study by ODECK (2009) evaluated technical efficiency and the MI with its decomposed components in combination with the bootstrapped confidence intervals as is done in this paper. When interpreting the results, one has to differentiate between an output-oriented and an input-oriented approach of calculating DEA measures. The approach depends on the point of view, whether farmers are to be considered input minimizers or output maximizers. However, either orientation allows an interpretation of resource efficiency, simply from different perspectives (BOGETOFT and OTTO, 2011; ODECK, 2009). It becomes apparent that the results of the studies strongly differ as they all evaluate different geographical regions and time periods. In contrast to most studies presented in Table 1, this paper is based on a balanced panel. Therefore, all data are available for all analyzed farm enterprises in each year considered, which improves the statistical analysis compared to unbalanced data sets with data gaps.

Table 1. Overview of recent studies using DEA or MI in combination with bootstrapping

Study	Country	Data set	Years	Orientation of model	DEA (VRS) Mean technical efficiency	Mean MI/ Mean TC/ Mean EC	Bootstrapped confidence interval (95%) technical efficiency	Bootstrapped confidence interval (95%) MI
BRÜMMER (2001)	Slovenia	147 mixed farms	1995-1996	Output-oriented	0.440	-	Average width of 0.09	-
BALCOMBE et al. (2008b)	Bangladesh	295 rice farms	2003	Output-oriented	0.590	-	0.530 – 0.630	-
LATRUFFE et al. (2008)	Poland	250 mixed farms	1996-2000	Input-oriented	-	0.980/ 0.940/ 1.040	-	0.770 – 1.310
ODECK (2009)*	Norway	19 crop farms	1987-1997	Input-oriented	0.893	1.380/ 1.210/ 1.120	0.830 – 0.949	1.100 – 1.770
MUGERA and LANGEMEIER (2011)	USA (Kansas)	564 mixed farms	1993-2007	Input-oriented	0.593	-	Average width of 0.043	-
ABATANIA et al. (2012)	Ghana	189 crop farms	2005	Input-oriented	0.859	-	0.625 – 0.854	-
HOANG LINH (2012)	Vietnam	595 rice farms	2003-2004	Input-oriented	0.785	-	0.593 – 0.771	-
SHAMSUDIN (2014)	Malaysia	147 rice farms	2011	Output-oriented	0.636	-	0.502 – 0.832	-

*Malmquist index (MI), change in technical efficiency (EC) and technical change (TC) scores are presented as inverse, i.e. 1.380 corresponds to 0.620 in input-oriented model
Source: Compiled and designed by author

Besides THIELE and BRODERSEN's (1999) study, which was described above, only very limited research has been conducted on technical efficiency and productivity change in the German agricultural sector. TIEDEMANN and LATACZ-LOHMANN (2011) compared productivity growth of organic and conventional German arable farms from 1999 to 2007 using an MI approach based on SFA efficiency scores. The conventional arable farms showed a mean annual productivity growth of 0.46 %, while organic arable farms showed a mean annual productivity deterioration of -0.58 %. According to the DEA approach of FRANCKSEN and LATACZ-LOHMANN (2006), the German agricultural sector had a technical efficiency of 0.917 under the assumption of variable returns to scale (VRS) and input-orientation between 1998 and 2001. Their MI analysis resulted in a mean annual productivity growth of 2.37 %.

3 Methodology

This section describes the three-stage methodological procedure carried out in this study. First year-by-year efficiency scores are obtained by applying DEA. The second step uses MI and its components in order to measure performance changes over time. Finally, bootstrapping as suggested by SIMAR and WILSON (1998, 1999) is applied to calculate confidence intervals for the obtained efficiency and productivity scores. The description of this methodology is mainly based on FÄRE et al. (1994; 2013), BOGETOFT and OTTO (2011) as well as ODECK (2009).

3.1 Data Envelopment Analysis

DEA is a linear programming method that estimates best practice production frontiers based on input and output data from a sample of DMUs for an individual year. It constructs a piece-wise linear surface over the different data points by solving a sequence of linear programming problems (BOGETOFT and OTTO, 2011; CHARNES et al., 1978; COELLI and RAO, 2005). In this study the individual farms each constitute a DMU. DMUs located directly on the frontier have an efficiency score of 1 (or 100 %). The efficiency score of all inefficient DMUs can be obtained from the distance from the frontier, whereby efficiency is measured in comparison with the nearest DMU on the frontier. This way each DMU's efficiency is measured in comparison with the most similar production structure from the data set (FRANCKSEN and LATACZ-LOHMANN, 2006). The DEA can either be input- or output-oriented. Consistent with SIMAR and WILSON's (1998) approach as well as other comparable studies (see table 1) input-oriented technical efficiency measures are calculated assuming variable (VRS) and constant returns to scale (CRS). The latter are necessary to further calculate MI as described in subsection 3.2. In an input-oriented context the DEA model minimizes the input vector while holding the output vector constant (BOGETOFT and OTTO, 2011). An input-oriented DEA model for the kth DMU under the assumption of VRS is defined as follows (BOGETOFT and OTTO, 2011):

$$\begin{aligned}
&\min_{\vartheta,\lambda} \vartheta \\
&s.t. \\
&-y_k + Y\lambda \geq 0 \\
&\vartheta x_k - X\lambda \geq 0 \\
&\sum_{k=1}^{K} \lambda_k = 1 \\
&\lambda \geq 0
\end{aligned} \tag{1}$$

The resulting efficiency score ϑ ranges between 0 and 1, λ constitutes a vector of multiplier weights and X and Y are matrixes containing all inputs x and outputs y. The convexity constraint $\left[\sum_{k=1}^{K} \lambda_k = 1\right]$ limiting the summation of the multiplier weights equal to one is necessary under the assumption of VRS. The DEA model assuming CRS is identical but without the convexity constraint (BOGETOFT and OTTO, 2011; ODECK, 2009).

3.2 Malmquist index

The MI is defined by input and output distance functions. It measures changes in productivity between two time periods. Distance functions can describe a multiple input and output technology without a specification of behavioral objectives such as cost minimization or profit maximization. In this study input-oriented MI are calculated in order to compare productivity growth across DMUs and years. Furthermore, productivity was decomposed into technical change (TC) and change in technical efficiency (EC). The MI between year t and year t+1 for inputs x and outputs y based on an input-distance function D_I is defined as follows (FÄRE et al., 1994):

$$M_I^t = \frac{D_I^t(x^{t+1}, y^{t+1})}{D_I^t(x^t, y^t)} \tag{2}$$

If M_I is less than 1, productivity growth is positive. FÄRE et al. (1994) further developed the model and showed that the geometric mean of the t and t+1 MI provides a better measure of productivity change between time periods t and t+1:

$$M_I^{t,t+1} = \left[\frac{D_I^{t+1}(x^{t+1}, y^{t+1}) D_I^t(x^{t+1}, y^{t+1})}{D_I^t(x^t, y^t) D_I^{t+1}(x^t, y^t)}\right]^{\frac{1}{2}} \tag{3}$$

Furthermore, they proved that equation (3) can be rearranged in order to provide the decomposition of productivity growth in TC and EC:

$$M_I^{t,t+1} = \underbrace{\frac{D_I^{t+1}(x^{t+1}, y^{t+1})}{D_I^t(x^t, y^t)}}_{EC} \times \underbrace{\left[\frac{D_I^t(x^{t+1}, y^{t+1}) D_I^t(x^t, y^t)}{D_I^{t+1}(x^{t+1}, y^{t+1}) D_I^{t+1}(x^t, y^t)}\right]^{\frac{1}{2}}}_{TC} \tag{4}$$

The ratio outside the brackets measures EC between time periods t and t+1, whereas the rest of the term measures TC. If $M_I^{t,t+1}$ has a value smaller than unity it indicates productivity growth, a value greater than unity indicates deterioration. The values of the components EC and TC are to be interpreted the same way. Given suitable panel data and under the assumption of CRS technology the distance functions for an individual DMU j referring to a single time period t or t+1 of equation (4) can be computed with DEA linear programming (FÄRE et al., 1994):

$$\left[D_I^t(x_j^t, y_j^t)\right]^{-1} = \min \vartheta^{t,t}$$
$$s.t.$$
$$\sum_{k=1}^{K} \lambda_k^t y_{mk}^t \geq y_{mj}^t, m = 1,...,M \quad (5)$$
$$\sum_{k=1}^{K} \lambda_k^t y_{nk}^t \leq x_{nj}^t \vartheta_j^{t,t}, n = 1,...,N$$
$$\lambda_k^t \geq 0, k = 1,...,K$$

The model assumes that there are $k = 1, \dots, K$ observations of $n = 1, \dots, N$ inputs x and $m = 1, \dots, M$ outputs y. The calculation of the distance functions referring to the two different time periods t and t+1 differs and reads as follows (FÄRE et al., 1994):

$$\left[D_I^t(x_j^{t+1}, y_j^{t+1})\right]^{-1} = \min \vartheta^{t,t+1}$$
$$s.t.$$
$$\sum_{k=1}^{K} \lambda_k^t y_{mk}^t \geq y_{mj}^{t+1}, m = 1,...,M \quad (6)$$
$$\sum_{k=1}^{K} \lambda_k^t y_{nk}^t \leq x_{nj}^{t+1} \vartheta_j^{t,t+1}, n = 1,...,N$$
$$\lambda_k^t \geq 0, k = 1,...,K$$

3.3 Bootstrapping of DEA and MI

After calculating efficiency scores and productivity indices we have to obtain the appropriate confidence intervals for them in order to make any reliable statements concerning the results' statistical significance. EFRON's (1992) approach to bootstrapping as suggested by SIMAR and WILSON (1998; 1999) has proven effective in examining the sensitivity of DEA efficiency scores and MI to sampling variation. It is based on the assumption that for a sample with an unknown DGP, the DGP can be estimated by developing a bootstrap sample using the original sample. In order to do so an empirical distribution of the relevant variables is constructed by sampling the original data set repeatedly generating an appropriately large number (B) of pseudo-samples. In this study 1 000 pseudo-samples (B=1 000) are generated as originally suggested by HALL (1986) to ensure adequate coverage of confidence intervals. Once a large and consistent estimator of the DGP is derived, the bootstrap distribution will imitate the original sampling distribution[1].

According to SIMAR and WILSON (1998) the bootstrap sample for DEA efficiency scores is expressed as $\left\{\hat{\vartheta}_{ib}^*\right\}_{b=1}^B$ with * denoting the bootstrap sample. An estimator's bias can now be estimated using the bootstrap sample as $\widehat{bias_i} = \bar{\vartheta}_i^* - \hat{\vartheta}_i$, with $\bar{\vartheta}^* = \frac{1}{B}\sum_{b=1}^{B} \hat{\vartheta}_{ib}^*$. Afterwards the bias corrected estimator for $\hat{\vartheta}_i$ can be expressed as (SIMAR and WILSON, 1998):

$$\tilde{\vartheta}_i = 2\hat{\vartheta}_i - \hat{\vartheta}_i^* \quad (7)$$

Furthermore, it is now possible to calculate (1-α)-percent confidence intervals for $\hat{\vartheta}_i$ using the empirical distribution of $\{\hat{\vartheta}_{ib}^*\}_{b=1}^B$ (SIMAR and WILSON, 1998):

$$\left(\hat{\vartheta}_{i,lower\ bound}, \hat{\vartheta}_{i,upper\ bound}\right) = \left(\tilde{\vartheta}_i^{*(\alpha)}, \tilde{\vartheta}_i^{*(1-\alpha)}\right) \quad (8)$$

SIMAR and WILSON (1999) showed that confidence intervals of MI[2] can be generated using the original estimates $\widehat{M}_I^{t,t+1}$ as well as bootstrap procedures resulting in the MI bootstrap sample $\{\widehat{M}_{t+1,k}^*\}_{b=1}^B$. The basis for this is the percentile method, which means obtaining the values a_α^* and b_α^* while holding the statement $prob\left(-b_\alpha^* \leq \widehat{M}_{t+1,k} - M_{t+1,k} \leq -a_\alpha^* \middle| y^j\right) \approx 1 - \alpha$ true with high probability conditioned on the original sample y^j. If $B \to \infty$ the probability approaches one. This step further allows an estimation of (1-α)-percent confidence intervals as follows (SIMAR and WILSON, 1999):

$$\hat{M}_{t+1,k} + a_\alpha^* \leq M_{t+1,k} \leq \hat{M}_{t+1,k} + b_\alpha^* \quad (9)$$

If these bootstrapped confidence intervals do not include the number one then the estimated MI statistically significantly differs from unity and therefore productivity growth (if smaller than 0) or deterioration (if greater than 0) is indicated. A more extensive description of the applied methodology can be found in BOGETOFT and OTTO (2011), ODECK (2009) and mainly in SIMAR and WILSON (1998; 1999). All calculations were performed in R using the FEAR package by WILSON (2008).

[1] The notations of the variables in this subsection are to be understood as follows: a hat denotes an estimated variable, an overscore denotes an empirical mean of a sample and a tilde denotes a bias-corrected variable.

[2] In accordance with the existing literature (cf. ODECK, 2009), the notation of the original MI model of FÄRE et al. (1994) is adapted to the notation of the bootstrap methodology of SIMAR and WILSON (1999).

Table 2. Main descriptive statistics for variables used (N=430)

	Crop output (€)	Arable land (ha)	Seeds/ planting material (€)	Fertilizer (€)	Crop protection (€)	Labor (WH)	Machine power (kWh)
Mean	854 026	490	52 020	102 772	91 214	5 175	330 356
Min.	121 017	81	6 177	12 798	12 375	545	20 352
Max.	3 669 057	2 187	185 496	495 264	422 091	17 850	1 870 501
Std. dev.	572 234	309	35 103	73 567	63 287	3 094	219 212

Source: Author's calculations

4 Data

This study is based on a balanced panel data set consisting of a sample of 86 German large-scale arable farms over a time period of five years. The assessed time period covers the fiscal years 2012/2013 to 2016/2017. The data was provided by a German agricultural management consultancy, which advises and analyzes all their farm enterprises annually. The 86 farms are geographically spread out over Germany with a majority located in the major crop producing regions of North, Central and Eastern Germany. All of them purely practice conventional crop farming (specialist cereals, oilseeds and protein crops) without a livestock branch or the cultivation of organic crops. Farms cultivating specialist permanent crops (e.g. wine or fruits) or specialist field vegetables (e.g. cabbage, asparagus) were already excluded in advance by the management consultancy providing the data.

Six input variables and one output variable were included in the DEA and MI models to assess technical efficiency scores and productivity change over time. Including too many input and output variables leads to a limitation of the DEA method. The approach loses its discriminatory power and therefore the ability to distinguish the better performers from the rest, as too many DMUs tend to be efficient.

Crop output in Euro (€) is used as output measure in the model[3]. It describes the monetary value of gross crop production on the evaluated farm and is given by adding the products of crop yield and crop market price of the different crops grown. Using the crop output for efficiency and productivity research in arable farming is a very common approach (cf. OUDE LANSINK et al., 2002; LATRUFFE et al., 2008; THIELE and BRODERSEN, 1999; BRÜMMER, 2001; FRANCKSEN and LATACZ-LOHMANN, 2006). Choosing the monetary crop output is advantageous regarding the comparability of the individual farms, since it can be calculated for each farm, while quantitative yields for different crops are not always equally available. The model's six input measures constitute the major input factors in crop farming. *Arable land in ha* is a farm's cultivated cropland, which is the productive net area without extensively used land or fallow land. *Seeds and planting material*, *fertilizer* as well as *crop protection* are measured as monetary values in Euro (€). The *labor (WH)* input is represented as working hours, which includes hired labor, owner's labor and family labor. The use of agricultural machinery is expressed in kilowatt hours (kWh) and introduced as *machine power (kWh)*. The selection of input variables for crop production is consistent with a wide range of existing research such as GOCHT and BALCOMBE (2006), BALCOMBE et al. (2008b) or MONCHUK et al. (2010).

Table 2 shows the main descriptive statistics for the seven variables used in this study. Mean, minimum, maximum and standard deviation are calculated for the assessed 430 observations. There is a high variation in the output as well in all input variables. With an average size of 490 ha, the farms considered here are far above the German average. Therefore, results should be interpreted as representing large-scale arable farms.

5 Results and discussion

In this section the methodology illustrated in section 3 is applied to the panel data set of German arable farms described in the previous section. To begin, the results of the static year-to-year efficiency score analysis are presented before the productivity change over time is assessed afterwards. The confidence intervals derived through bootstrapping in order to account for statistical significance are also presented in the corresponding sections.

[3] Farm subsidies were not taken into account in this context to solely assess the arable primary production.

Table 3. Summary results of original and bootstrapped efficiency scores (VRS) (N=430)

	2012/13	2013/14	2014/15	2015/16	2016/17	Mean full period
DEA scores						
Mean	0.887	0.901	0.920	0.912	0.920	0.908
Min.	0.624	0.667	0.409	0.625	0.618	0.589
Std. dev.	0.108	0.098	0.102	0.101	0.093	0.100
Number of DMUs with an efficiency score of 1	25	25	34	32	31	-
*Bootstrap sample**						
Mean	0.887	0.901	0.920	0.912	0.920	0.908
Bias corrected mean	0.834	0.854	0.872	0.868	0.876	0.861
Std. dev.	0.041	0.037	0.038	0.037	0.037	0.038
Bias corrected confidence interval, 95 %						
Lower bound	0.782	0.803	0.820	0.816	0.823	0.809
Upper bound	0.883	0.898	0.917	0.909	0.917	0.905

* based on 1 000 pseudo-samples
Source: Author's calculations

5.1 DEA efficiency scores

As described in the methodology section the input-oriented technical efficiency scores are calculated using DEA under the assumption of VRS and CRS. However, the CRS efficiency scores are only necessary for the assessment of productivity change, which is described later on. Since a CRS assumption is only adequate if all DMUs work at an optimal scale, the VRS assumption, which was introduced by BANKER et al. (1984) is the more appropriate model to use if there are good reasons to assume that the technology to be estimated exhibits variable returns to scale. Limitations such as imperfect competition or a factor constraint might lead to a DMU not operating at optimal scale (HARTWICH and KYI, 1999). Table 3 shows the summary results of the original and bootstrapped efficiency scores under the assumptions of input-orientation and VRS. As described earlier, an input-oriented technical efficiency score minimizes the degree to which input factors proportionally have to be reduced in order to produce the same output in a technically efficient manner or – in other words – it measures the potential for input savings. The upper panel of the table shows the original non-bootstrapped efficiency scores. The mean[4] efficiency score across the five-year time period is 0.908, which indicates an input saving potential of 9.2 %. The mean efficiency scores of the individual years range between 0.887 and 0.920. The minimum of the original efficiency scores presents the DMU with the highest input saving potential. The mean of the minimums across all five years is an input saving potential of 41.1 %. It is notable that 2014/2015 as the year with the highest mean efficiency score also shows the lowest minimum. The mean standard deviation of the original efficiency scores over the assessed time period is 0.100, with all individual years ranging close by. The results of the original efficiency scores indicate a high degree of homogeneity regarding technical efficiency in the sample, even though the farms' input and output variables vary greatly as illustrated in table 2. A possible explanation for the high level of technical efficiency as well as said homogeneity lies within the source of the assessed data. Since the farms all receive economic advice from an agricultural consultancy, above-average efficiency can be expected.

The mean efficiency score, the bias corrected mean of the efficiency score and the standard deviation of the efficiency score for the bootstrapped sample are presented in the middle panel of table 3. The bootstrap sample consists of 1 000 pseudo-samples as described in the methodology section. The average mean across the assessed time period is 0.908 just as it is for the original sample. However, the standard deviations of the mean efficiency scores are less than half the level of the original sample. The bias correct-

[4] Technical efficiency scores are not interval-scaled with regards to the input-saving potential, therefore one has to be careful when considering means of technical efficiency, as these would normally require a metric scale. Deeper insights into scale levels and the interpretation of technical efficiency scores are provided by STEVENS (1946) and MUSSHOFF et al. (2009). In accordance with the existing literature the means were nevertheless shown in this study.

ed means for the individual years as well as the across time period average are notably lower than the regular estimate. Results show there is a positive bias for the bootstrapped sample. Regarding the bias, this study's results differ from ODECK's (2009) research on Norwegian grain farms, which indicated that bias changes for the data set as a whole are negligible.

In the lower panel of table 3 the bias corrected 95 % confidence intervals for the bootstrapped sample are presented. SIMAR and WILSON (1998) state that caution should be observed when comparing performance based on original efficiency scores. If there is an overlap between the confidence intervals of two different efficiency scores, one may not assume that they differ even if the original scores do. On this basis the fluctuations between the mean technical efficiency scores of the individual years cannot be confirmed with statistical significance as their confidence intervals across all five years heavily overlap. To check the robustness of the results, the model was also calculated with four input variables (the monetary inputs seed, fertilizer and crop protection were combined into one variable). The results show that although the overall level of the efficiency scores decreases slightly due to the lower number of inputs, the core statements and dimensions remain unchanged.

To illustrate the importance of deriving confidence intervals when comparing performance based on original efficiency scores, a selection of individual farm data is presented in table 4. The farms 1, 35 and 47 were selected as their results are suitable to demonstrate the issue. For instance, when comparing farm 1 and farm 35, their mean original efficiency scores indicate that farm 35 is more efficient as 0.936 is larger than 0.871. Looking at the respective confidence intervals derived through bootstrapping this statement can be considered true with a probability of 95 %. The 95 % confidence intervals do not overlap. When comparing farm 1 and farm 47, the initial judgment is the same. The mean original efficiency scores indicate that farm 47 is more efficient than farm 1. However, since their respective confidence intervals overlap, the statement cannot be supported statistically in this case.

5.2 Malmquist productivity indices

After discussing the efficiency scores in the preceding section, the focus is now on TFP change and its components over the assessed period from 2012/13 to 2016/2017. As further described in the methodology section, input-oriented MI are calculated through DEA in order to compare productivity growth in German arable farming across years. Furthermore, productivity is decomposed into technical change (TC) and change in technical efficiency (EC). The DEA model used to assess MI, EC and TC assumes CRS, since GRIFELL-TATJÉ and LOVELL (1995) showed that under the assumption of non-constant returns to scale productivity change is not measured accurately by MI. Table 5 shows the summary results of annual productivity change and its components for the original sample. The results constitute the annual averages across DMUs and time periods. Note that in the context of MI, EC and TC all averages are by definition geometric means (FÄRE et al., 1994). Under the assumption of input-orientation, values below one indicate growth and values above unity represent deterioration.

Table 5. Mean MI, EC & TC for original sample, 2012/13 - 2016/17 (CRS)

	Malmquist index (MI)	Efficiency change (EC)	Technical change (TC)
Mean	0.946	1.011	0.935
Min.	0.873	0.935	0.874
Max.	1.056	1.099	0.999
Std. dev.	0.035	0.032	0.019

Source: Author's calculations

Looking at the means across all units and time periods of the original sample, the TFP grew annually by 5.4 % on average. The advantages of the decomposable

Table 4. Original efficiency scores and bootstrap of efficiency scores across selected DMUs and time (VRS)

DMU	Original efficiency scores per year					Over the full period				
	2012/13	2013/14	2014/15	2015/16	2016/17	Mean	Bootstr. mean	Bias corr. mean	Lower bound	Upper bound
1	0.833	0.941	0.963	1.000	0.618	0.871	0.871	0.833	0.783	0.868
35	0.956	0.909	0.951	0.911	0.952	0.936	0.936	0.903	0.876	0.933
47	0.861	1.000	1.000	1.000	1.000	0.972	0.972	0.903	0.826	0.969

Source: Author's calculations

productivity measure MI become apparent as one is able to specify what drove the productivity change. For the original sample TFP growth was driven by an average growth rate in TC of 6.5 %, which outweighed a slight average deterioration of EC (1.1 %). The minimums indicate the farms with the largest increases in MI, EC and TC, while the maximums indicate the smallest increases in these measures. 12.7 % was the largest average annual growth in TFP achieved by a single DMU. Only seven out of 86 farms (8.1 %) experienced an average annual deterioration of TFP over the assessed time period with 5.6 % p.a. marking the weakest DMU. 47 farms (54.7 %) experienced an average annual deterioration of efficiency change. EC, which describes catching-up towards the existing efficiency frontier or in other words growing input savings, was therefore not a contributing factor towards productivity growth. This result is not contradictory to the high level of technical efficiency calculated from the static point of view (subsection 5.1) as the dynamic MI describes a different perspective. A DMU can show high technical efficiency for single time periods and still show deterioration in EC when plotting the development over time. This finding is in line with the results of LATRUFFE et al. (2008) for Polish farms. Technical change, which describes a shift with regards to a DMU's input mix (innovation), was the driving factor of TFP growth. Every single farm in the sample experienced average annual growth in TC, indicating an adoption of input saving techniques (ODECK, 2009). This component also shows a low standard deviation (0.012), which suggests a homogenous average level of innovation. The increasing use of input-saving precision farming techniques is assessed in multiple studies. For instance, PAUSTIAN and THEUVSEN (2017) conducted a survey which showed that 69 % of German large-scale arable farms (> 500 ha) from their sample are precision farming adopters. Their findings of a statistically significant effect of farm size on adoption of input-saving techniques are congruent to BARNES et al.'s (2019) cross regional study of EU farms.

Table 6 shows period by period developments of mean MI, EC and TC over the observation interval for the original sample. Strong fluctuations are visible when comparing the four observed time periods. The first three time spans all show TFP growth, only the period from 2015/16 – 2016/17 shows deterioration in MI (5.1 %). In this period both components of the MI deteriorated as well. Possible explanations are the more disadvantaged weather conditions for German arable farms in 2016/17 as opposed to 2015/16 as well as the decline in agricultural commodity prices over said time period. Both occurrences lower the output variable of this study's model and thus productivity if the amount of inputs is not reduced proportionally. In addition, bad weather conditions during the year of cultivation tend to lead to increased input costs (SMIT et al, 1996). The largest gain in TFP (16.0 %) is observed between 2013/14 and 2014/15, despite a 1.9 % deterioration in EC. The large growth in TC (17.5 %) indicates a high adoption of input saving techniques in that time period for the farms in the original sample.

Table 6. Mean MI, EC & TC for original sample (CRS) (N=86)

Time period	Malmquist index (MI) mean	Efficiency change (EC) mean	Technical change (TC) mean
2012/13–2013/14	0.992	1.020	0.972
2013/14–2014/15	0.840	1.019	0.825
2014/15–2015/16	0.913	0.989	0.923
2015/16–2016/17	1.051	1.016	1.035
Mean over the full period	0.946	1.011	0.935

Source: Author's calculations

Table 7 shows the mean 95 % confidence intervals across DMUs and time periods which were derived through bootstrapping according to SIMAR and WILSON (1999). If a bootstrapped confidence interval does not include the number one, the estimated MI statistically significantly differs from unity and therefore productivity growth (if smaller than 0) or deterioration (if greater than 0) is indicated. The bootstrapped confidence intervals of EC and TC are to be interpreted the same way regarding their respective development. The MI shows significant progress at the 5 % level as the confidence intervals range from 0.914 to 0.981. This interval will, if repeated infini-

Table 7. Mean 95 % confidence intervals for MI, EC and TC for bootstrap sample, 2012/13 - 2016/17 (CRS)

	Malmquist index (MI)	Efficiency change (EC)	Technical change (TC)
Lower bound	0.914	0.935	0.885
Upper bound	0.981	1.086	0.997

Source: Author's calculations

tively, include the true value of TFP growth in any sample drawn from the statistical population for the assessed time period 95 % of the time. The confidence interval for the technical change component (0.885, 0.997) does not contain unity either, so that statistically significant growth over the observed period can be concluded. In contrast, the confidence interval for EC (0.935, 1.086) includes unity. Therefore, on this basis it is not possible to conclude statistically significant whether there is growth or deterioration. This is not very surprising, since the mean EC for the original sample (1.011) ranges very close to unity. The bootstrapped confidence intervals demonstrate once more why one has to be careful when solely considering results from the original sample. Bootstrapping allows for more robust conclusions and enables a higher degree of generalization (ODECK, 2009). The results reveal a large amount of uncertainty regarding productivity change and its components in German large-scale arable farming. The indicated uncertainty is consistent with the finding of LATRUFFE et al. (2008) for Polish farms and underscores SIMAR and WILSON's (1999: 471) concluding argument that "it is not enough to know whether the Malmquist index estimator indicates increases or decreases in productivity, but whether the indicated changes are significant in a statistical sense; i.e., whether the result indicates a real change in productivity, or is an artifact of sampling noise."

6 Concluding remarks

This study aims to contribute to the existing research on efficiency and productivity measurements in the agricultural sector. Further insights into technical efficiency and therefore a better understanding of the efficient utilization of limited inputs is needed if the agricultural sector's output is to keep up with the increasing global demand for food and raw materials. This study contributes to this understanding by first determining the degree of technical efficiency in German large-scale arable farming. Further, it evaluates the magnitude of productivity change in German large-scale arable farming and discusses whether it is mainly due to changes in technical efficiency or changes in technology for a time period that has not been evaluated until now. In this context this study aims to provide statistical evidence regarding efficiency and productivity measurements for German large-scale arable farms and to illustrate the bootstrapping procedure of DEA and MI results in an agricultural application.

The raised research questions are evaluated using a panel data set of input and output variables for 86 German large-scale arable farms over a time period from 2012/2013 to 2016/2017. Year-by-year efficiency scores are obtained by applying DEA. Afterwards the MI and its components are calculated in order to measure performance changes over time. Finally, bootstrapping as suggested by SIMAR and WILSON (1998, 1999) is applied to calculate confidence intervals for the obtained efficiency and productivity scores. This enables more robust conclusions regarding the statistical significance of the findings.

The DEA results from the original sample show a mean input-savings potential of 9.2 % across farms and time periods. The fluctuations between the five assessed fiscal years are minimal with an overall positive trend. The results of the original efficiency scores indicate a high degree of homogeneity regarding technical efficiency in the sample, even though the farms' input and output variables highly vary. The bootstrapped confidence intervals suggest no statistically significant difference among the mean scores for individual years, however significant differences exist between individual DMUs. The results of the MI analysis from the original sample indicate a mean annual growth rate in TFP of 5.4 %. This progress was driven by growth in TC (6.5 %) and happened despite a small average deterioration in EC (1.1 %). The results further suggest a homogenous average level of innovation for the increasing adoption of input-saving techniques. The progress in TFP and TC is statistically underpinned through the bootstrapped confidence intervals. The result of EC computed from the original sample cannot be confirmed statistically as the corresponding confidence interval includes unity. The mean MI, EC and TC for individual time periods show large fluctuations between the four year-to-year time periods. The finding that original efficiency and productivity measures might indicate no statistically significant results is consistent with previous studies applying bootstrapping techniques.

Considering the average German arable farm structure, it might be useful to repeat the analysis with smaller farms to obtain a representative sample. Further limitations are price effects on the chosen output variable as well as the high degree of homogeneity among the evaluated farms. This paper's results also provide starting points for further research. The derived scores and developments of efficiency and productivity in German large-scale arable farming could be complemented with an analysis of the factors that affect the scores. This could enable a better classification of the evaluated farms and help identify efficiency and productivity drivers. Assessing the influence of price changes for monetary input and output variables, socio-demographic farm characteristics and especially the adoption of precision agriculture technology could add to a deeper understanding regarding efficiency and productivity change in German arable farming.

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