Development of Total Factor Productivity in Alpine Farming

- A Malmquist index approach -

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Summary

In comparison to flatland agriculture mountainous agriculture is often shaped by small plot sizes, unfavourable climatic conditions and steep slopes. All those conditions make it extraordinarily expensive to implement new technologies and to modernise farms. Consequently our research hypothesis is that technical progress in mountainous regions is slower in comparison to flatland regions. In order to test this hypothesis we develop a model combining a Malmquist index approach with a matching analysis. We apply our model in Austria, using a panel data set comprising the data of 1034 Austrian voluntarily bookkeeping farms and ranging from 2003 to 2009. On basis of the Austrian Mountain Farm Cadastre the farms are classified into five categories expressing the degree of disadvantage which farms are exposed from being located in a mountainous area. Our results show that technical change in mountain regions is significantly lower than in flatland regions and continuously decreasing with increasing disadvantage. Matching our results shows that this result is mainly based on farm grassland share, while farm size is of minor importance. With regard to efficiency change and change of total factor productivity we do not find any significant results.

Keywords: Malmquist total factor productivity index, technical progress, Alpine farming, data envelopment analysis, matching

JEL Classification codes: C14, C67, Q12

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1. Introduction

Site conditions for Austrian agriculture are very heterogeneous. In particular, the difference between mountainous areas and flatland areas is shaping Austrian agriculture. In comparison to flatland agriculture, mountainous agriculture in general is characterized by small plot sizes, unfavourable climatic conditions and steep slopes. Therefore it is extraordinarily expensive to implement new technologies. Consequently our research hypothesis is that technical progress in mountainous regions is slower in comparison to flatland regions.

In order to answer this question we apply a Data Envelopment Model (DEA). DEA is suitable method allowing the economic performance of farms to be assessed (Charnes et al. 1978). A notable strength of DEA is that it allows for the consideration of multiple inputs and outputs while not requiring identical units. There are a number of studies which analyse farm performance with the help of DEA. For instance, Balmann and Czasch (2001) calculate and compare the economic efficiencies of East German farms. Reig-Martinez and Picazo-Tadea (2004) estimated the economic efficiencies of Spanish citrus farms in order to identify best-practice farms.

Based on the DEA we apply a Malmquist Total Factor Productivity (TFP) index model. In contrast to DEA efficiency scores are calculated not only for a single year but for several years and efficiency change rates can be determined. Finally we match the results we received with the Malmquist model. Matching goes back to the work of Rubin (1977). It allows us to compare TFP index results of farms located in mountainous areas with the TFP index results of farms which are located in flatland areas but nevertheless are fairly similar with regard to structural aspects.

The remainder of our paper is organized as follows: In Section 2 we present our methodical framework, define the required economic input and output variables and introduce our data basis. The results of our Malmquist TFP index calculation and of our matching analysis are displayed in Section 4. Finally, in Section 5, we discuss our results and draw some conclusions for the further development of our model.

2. Method und Data

The first part of the following section contains a description of the methods applied in our empirical analysis, namely Data Envelopment Analysis, the Malmquist Total Factor Productivity index and Matching. We introduce the applied methods only very briefly, since all methods itself are well-known and well-described in literature. However, further information on the applied methods can be found in the indicated references.

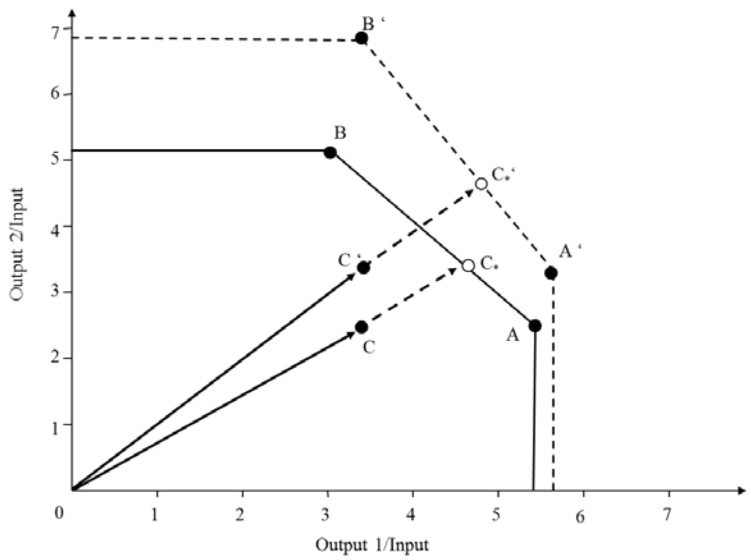
In the subsequent parts of the section we define input and output variables of our model and present the data base. In this context we also introduce the Austrian *Berghöfekataster* (BHK, mountain farm cadastre) system, which classifies farms with regard to their potential economic disadvantage caused from being located in a mountainous area.

2.1. Method

The main aim of our study is to analyse whether the technical change of mountain farms differ from the technical change of a flatland farms. In order to do so we apply a Malmquist Total Factor Productivity index. The TFP approach is based on Data Envelopment Analysis, which will be briefly described in the following paragraphs. DEA, which was originally developed by Farell (1957), is a non-parametric mathematical programming approach. It enables the comparison of production performances of so-called Decision-making Units (DMU). In our case these DMUs are farms deciding on the use of production factors in order to maximise farm output. The performance of each farm is rated by calculating the output-to-input ratio of the respective production processes; the less input a farm requires for producing a given output or the more output it produces with a given input, the higher is the productivity of the farm. The final efficiency score is derived by benchmarking the output-to-input ratio of an individual farm against the output-to-input ratio of all best-practice farms.

Figure 1, which is based on a single-input/double-output case, explains this principal idea of DEA: In period I (refer to the continuous lines in Figure 1) farms A and B show the longest distance to the origin. Consequently these farms are determined as best-practise farms, which form the so-called data envelope (cf. fig. Cooper et al. 2007). This envelope serves as a reference frontier allowing to benchmark all those farms which do not reach the frontier. In our case, the efficiency of C is calculated by comparing the distance from the origin 0 to the actually observed point C and the distance from the origin 0 to the potentially possible point C*.

Figure 1: Input-output analysis



Annotation: continuous line indicates period I, dashed line period II
Source: own illustration

Cooper-Rhodes model (Cooper et al. 2007, p. 42). Since the main (economic) goal in agriculture is to maximize output rather than to minimize input, we apply the output-orientated version of this model (cf.

Coelli and Rao, 2003). However, it should be emphasized that with either output or input orientation the technical efficiency scores will be the same unless a variable returns to scale model is applied.

The linear programming problem to be solved for each farm is as follows:

$$\begin{aligned} &\max_{\phi,\lambda} \phi \\ \text{s. t.} \quad & -\phi y_i + Y\lambda \geq 0 \\ & x_i - X\lambda \geq 0 \\ & \lambda \geq 0, \end{aligned} \tag{1}$$

where ϕ is a scalar, λ is a Nx1 vector of weights, X is a NxK matrix of input quantities for all N farms, Y is a NxM matrix of output quantities for all N farms, xi is a Kx1 vector of input quantities for the i-th farm and yi is a Mx1 vector of output quantities for the i-th farm. In order to derive the technical efficiency θ, expressing the performance of the studied farms, the reciprocal of ϕ has to be calculated. In DEA the relevance of input (X) und output variables (Y) is expressed by weights (η in the input case, μ in the output case), which are determined in a way that the assessed DMU achieves the highest possible level of efficiency. In order to derive input weights η and output weights μ, additional to the above described envelopment model the multiplier model has to be solved (cf. Cooper et al. 2007, p. 42).

In a second step we apply a Malmquist Total Factor Productivity Analysis. This method is based on DEA, but efficiency scores are calculated not only for one single time period but for several time periods. On this basis efficiency scores can be compared among farms as well as the change of efficiency scores within the observed period can be calculated. Again Figure 1 serves to illustrate this idea: Due to technical progress the output of all farms increases and observation points move away from the origin. In consequence of this also the frontier (the data envelop) moves outwards: In the new period it is formed by A* and B* (and symbolised by the dashed curve). However, although C doubtlessly also increased output and shifts to the new observation point C*, the new efficiency of C* must not increase in any case. If the shift of the frontier (which can be interpreted as the technical change) is bigger than the shift of the specific farm, this will result in a negative efficiency change. In other words, the algebraic sign of the efficiency change depends on the movement of the specific observation point and on the movement of the frontier. In order to assess the efficiency change of the specific farm, both aspects, namely efficiency change and respective technical change, are combined in one measure: the so-called total factor productivity change.

From the mathematical point of view the Malmquist TFP index is calculated as follows:

$$m_o(y_s, x_s, y_t, x_t) = \left[\frac{d_o^s(y_t, x_t)}{d_o^s(y_s, x_s)} \times \frac{d_o^t(y_t, x_t)}{d_o^t(y_s, x_s)} \right]^{1/2}, \tag{2}$$

where the notation dos(yt, xt) stands for the distance from the period t (the future period) observation to the period s (the base period) technology (Coelli and Rao, 2003). Alternatively the writing of this productivity index is

$$m_o(y_s, x_s, y_t, x_t) = \frac{d_o^t(y_t, x_t)}{d_o^s(y_s, x_s)} \left[\frac{d_o^s(y_t, x_t)}{d_o^t(y_t, x_t)} \times \frac{d_o^s(y_s, x_s)}{d_o^t(y_s, x_s)} \right]^{1/2}, \tag{3}$$

where “the ratio outside the brackets measures the change in the output-oriented measure of Farrell technical efficiency between periods s and t. That is, the efficiency change is equivalent to the ratio of the technical efficiency in period t to the technical efficiency in period s. The remaining part of the index in equation 2 is a measure of technical change. It is the geometric mean of the shift in technology between the two periods” (Coelli and Rao, 2003).

As last step, we apply Matching in order to compare the efficiency results of only such farms, which are comparable in structural aspects. Matching goes back to the work of Rubin (1977) and is mainly applied in studies, where an estimation of causal effects of a certain policy measure is done. In order to assess causal effects in observational studies a naïve comparison of treated and non-treated units leads to a biased results. That's because there are certain variables, which correlate to the assignment to one of these groups as well as to the outcome and consequently confound the causal effect (Imbens and Wooldridge, 2009). One way to cope with this problem of confoundedness is to apply econometrical and statistical methods. One of the most promising and well-studied methods is matching, which basically conditions on observable determinants of the assignment to one of these groups (Morgan and Winship, 2010, 81f).

In our case we do not use the matching approach for assessing policy measure but to find our set of mountainous farms a set of flatland farms which are comparable with in structural aspects. In order to do this we apply a matching model which is based on the nearest neighbour approach. This means that we identify for each treated unit a non-treated (control) unit with the smallest distance with regard to the respective observable variable. We identify the nearest neighbors by matching directly on the chosen variables. This approach – which is called Direct Covariate Matching (DCM) – represents the most straightforward non-parametric matching procedure. However, the approach is limited applicable if the number of variables rises (Sekhon, 2009). This shortcoming states no problem for our analysis since we concentrate on very few structural variables. Namely we use farm size (UAA) and grassland share, since these variables represent the most important structural differences in our data set.

2.2. Definition of input and output variables

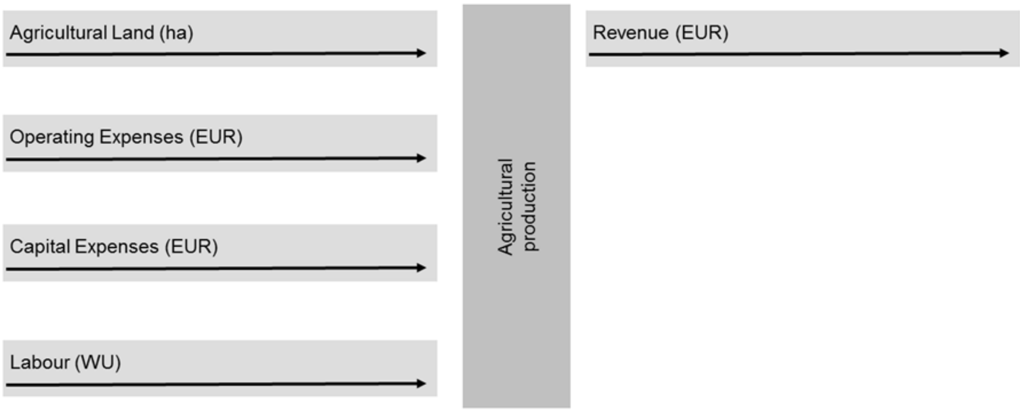
Using DEA for the assessment of farms, we have to define appropriate input and output factors. A fundamental requirement doing this is that the factors have to cover the full range of resources used. Moreover, all relevant activity levels and performance measures have to be captured (Dyson et al. 2001). However, the number of input and output variables has to be kept at a distinctly smaller level than the number of DMUs (or farms, respectively). Otherwise, too many DMUs will appear efficient and no relevant conclusions can be drawn. To minimize the number of variables to a suitable ratio with respect to the number of DMUs, the variables have to be aggregated. Dyson et al. (2001) suggest in this context that the number of DMUs should be at least twice the product of the number of input variables and the number of output variables.

In our paper we consider agricultural land and other economic inputs and relate them to economic output. The resulting efficiency measure expresses the economic success of the farm and therefore represents the performance of farmers. It shows how much input a farm needs in order to produce economic output (revenue). As input variables we use the agricultural land (ha), the operating expenses (EUR), the capital expenses (EUR) and the labour (WU). As output variables we use the farm revenue (EUR). It is to annotate that all monetary values are deflated. Figure 2 gives an overview of the selected input and output variables.
All input and output variables are briefly described in the following enumeration:

- Agricultural land summarizes all grassland and arable land cultivated by farms. It is measured in hectare.
- Capital expenses summarise the expenditures for fixed assets such as machinery and buildings. In order to reflect the yearly expenses, the value of capital assets is depreciated (cf. BALMANN and CZASCH, 2001). They variable is expressed in Euro

- Operating expenses are all expenses which are directly related to the production of the farm. In particular, they include the costs for energy (fuel and power supply), plant protection, fertilizers, fodder and hired machinery. This variable is expressed in Euro.
- Labour considers agricultural work provided by family members and employees; hired machine work is not included in this factor. Labour is expressed in Working Units (WU).
- As output variable we use the revenue. This factor considers all revenues of the farm from animal and crop production. Furthermore, all subsidy payments granted to the farm are considered. These include the payments for agri-environmental programmes, less-favoured area payments, as well as direct payments of the European Union. This variable is expressed in Euro.

Figure 2: Definition of input and output variables



Source: own illustration

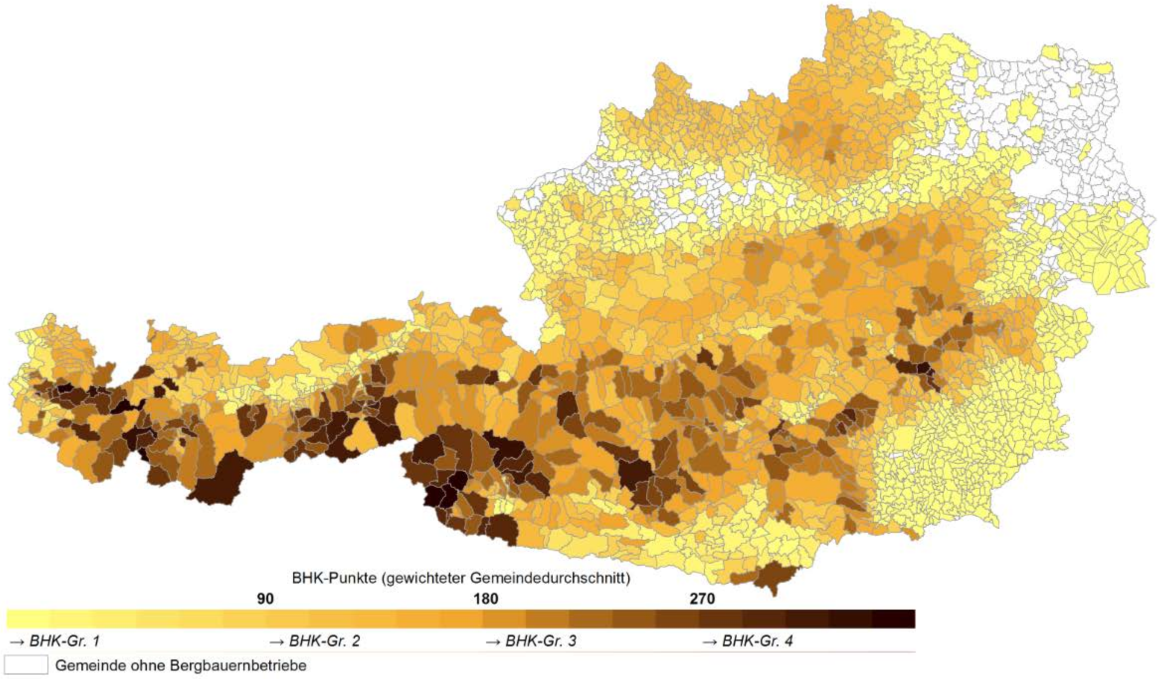
2.3. Definition and description of data

We apply the model on an Austrian farm panel data set. The set comprises data of 1034 voluntary bookkeeping farms and range from the year 2003 to the year 2009. In order to ensure a principal comparability of farms, we consider only cash-cropping, pig and poultry, mixed and forage farms, and exclude other farm types such as permanent crop and gardening farms.

As a basis for the classification of farms with regard to their belonging to the mountainous area, we use the Austrian Mountain Farm Cadastre (BHK). It allows the estimation of the degree of disadvantage which farms are exposed from being in a mountainous area. The cadastre classifies mountain farms into four categories and is calculated on the basis of the following indicators (the percentage in brackets indicates the respective relevance of the factor for the calculation of the BHK degree): steepness of slopes (49 %), accessibility (18 %), temperature (9 %), sea level (9 %), soil fertility (9 %) and average plot size (7 %).

Figure 3 depicts the spatial distribution of average BHK classes in Austria. It becomes clear that in particular the western parts of Austria which are shaped by the Alps are dominated by high BHK classes. The eastern parts are comparatively flat and they consequently show quite low BHK classes. However, also the *Waldviertel* region in the north-eastern part of Austria is characterised by comparatively high BHK classes.

Figure 3: Spatial distribution of BHK classes in Austria



Source: own illustration based on IACS (2009)

Table 1 presents our empirical data. The data set is grouped into the five BHK groups 0, 1, 2, 3, 4. For each group the respective group size (number of farms) as well as mean and variation coefficients of all input and output variables are displayed.

Table 1. Mean (and coefficient of variation) of selected input and output variables

	BHK 0	BHK 1	BHK 2	BHK 3	BHK 4
Number of farms	406	218	280	87	43
Utilised Agricultural Area [ha]	26 (0.88)	31 (0.96)	29 (0.70)	42 (0.93)	38 (0.88)
Labour [WU]	1.6 (0.39)	1.6 (0.37)	1.6 (0.35)	1.7 (0.29)	1.4 (0.41)
Capital assets [EUR]	214,748 (0.62)	279,942 (0.72)	281,941 (0.60)	264,587 (0.52)	233,058 (0.61)
Financial expenses [EUR]	38,325 (0.89)	30,108 (0.65)	27,310 (0.62)	22.276 (0,59)	16.979 (0,63)
Revenues [EUR]	64,965 (0.78)	55,153 (0.61)	50,275 (0.60)	41,391 (0.59)	29,819 (0.71)

Annotation: all data refer to the first year of the observation period (2003)
Source: own calculations

The data show that the BHK groups 0, 1 and 2 are each represented by more than 200 farms. The BHK groups 3 and 4 are significantly smaller. However, with a size of more than 40 farms they are still big enough to be included into our analysis. With regard to UAA is becomes clear that the farms of BHK groups 3 and 4 are in average bigger than the farms of all other groups. Labour differs only in the BHK 4 group from the other groups; they are in average equipped with less working units. Capital assets are higher in

BHK 1, 2 and 3 and comparatively low in the BHK groups 0 and 4. A clear ranking exists with regard to financial expenses: the higher the BHK number, the lower are financial expenses. The same applies for revenues; also here average revenues are decreasing with increasing disadvantage. The coefficient of variation is in all cases (with exception of labour) comparatively high. This indicates that farm samples are quite heterogeneous with regard to the most variables.

3. RESULTS

The technical change, expressed by the outward shift of the DEA frontier, can be interpreted as an efficiency increase which most efficient farms in our sample realised in the observed period. Regarding the results of our analysis depicted in Table 2, we observe that the technical change of mountain farms is significantly lower than the technical change of flatland farms. The less disadvantageous agricultural site conditions are, the more the DEA frontier shifts. If we now understand the DEA frontier as the state-of-the-art technology and the shift of the frontier as the velocity of the technical progress, one can state, that flatland farming systems benefit in comparison to mountainous agriculture from a faster technical progress.

Table 2. Mean technical efficiency change, technical change and total factor productivity change

	BHK 0	**BHK 1**	**BHK 2**	**BHK 3**	**BHK 4**	**signific.**
Technical change	1.037	1.036	1.031	1.026	1.021	***
Efficiency change	0.967	0.974	0.975	0.983	0.977	-
Total factor productivity change	1.003	1.009	1.005	1.008	0.997	-

Annotation: Kruskal-Wallis-H-Test; Significance levels: *< 0.05; **< 0.01; ***< 0.001;
Source: own calculations

Coming from that point one may also think about the ability of the “average farm” to follow the technical progress. If we consider that the implementation of new technologies is costly, one can conclude that it will be increasingly difficult for an average farm to follow the technical progress the quicker the technical progress takes place. With regard to our analysis this would mean that a quick technical change should be accompanied by a small change in total factor productivity. However, according to Table 2 we do not find any significant results with regard to TFP change, so we cannot prove this thesis. Table 2 indicates furthermore no significant differences between the various BHK groups with regard to efficiency change.

In order to assess causal effects in observational studies a naïve comparison of treated and non-treated units leads to a biased results. The consequence for our analysis is that a simple comparison of the different BHK groups is not sufficient as other attributes beside of the degree of disadvantage may influence the technical change: e.g. there might be a faster biological technical progress in crop farming than in husbandry. According to the design of our TFP model design we are not able to determine whether the difference in technical change results from the degree of disadvantage or other farm-specific attributes which correlate to the location of the holding.

In order to cope with this problem we match in a second step our Malmquist TFP model results. As Table 3 shows the detected differences with regard to technical change disappear and lose significance. This applies in particular if we match with regard to farm grassland share, while farm size is of minor importance. These results indicate that the reduced rate of technical change does not depend so much on the circumstance of being in a mountainous area and encountering all the typical disadvantages such as unfavourable weather conditions and relief, as well as small plot sizes, but much more on being forced to work with a comparatively high share of absolute grassland.

Table 3. Naïve and matched comparison of BHK 0 and BHK … results with regard to technical change

	BHK 1	BHK 2	BHK 3	BHK 4
Naïve comparison	-0.001	-0.006**	-0.012***	-0.017*
Matched comparison - LF	-0.002	-0.005***	-0.008**	-0.012**
Matched comparison - %DF	0.002	-0.002	-0.001	-0.008
Matched comparison - LF+%DF	0.003	-0.003	-0.003	-0.004

Annotation: Mann-Whitney-U-Test; Significance levels: *< 0.05; **< 0.01; ***< 0.001;
Source: own calculations

4. Discussion and Conclusions

From the methodical point of view, we conclude that the Malmquist TFP index approach is a suitable way to analyse the technical change of farming systems. Our results show that the technical change in Austrian agriculture is in average the higher the less disadvantageous the site conditions for farms are. However, we cannot prove the thesis that in regions with low technical progress farms can easier follow the technical change whereas in regions with high technical progress a segregation of farms into two groups takes place: into a group of farms which determine technical progress and into another group which cannot follow the technical progress. With regard to this point it is to state that our model only allows us to get a first insight. In order to come to more reliable results a deeper analysis of each BHK group is necessary. A possible track would be to calculate for each BHK group a separate TFP model. However, the challenge of such an approach would be to establish a comparability of the resulting efficiency change rates.

With regard to the applied methodology we can further conclude that the combination of the TFP index with matching allows an in-depth analysis of the factors which drive the differences in technical progress between the considered BHK groups. Consequently we plan to continue this approach. Furthermore, in order to get results which are closer to production and more independent from markets, we plan to adapt our model by including production-related non-monetary input and output variables. Another challenge is to deal with random variations in yields, which have a high influence in plant production but not in animal husbandry.

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