Dairy farming on permanent grassland: Can it keep up?

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ABSTRACT

Based on an extensive data set for southern Germany, we compared the productive performance of dairy farms that operate solely on permanent grassland and dairy farms using fodder crops from arable land. We allowed for heterogeneous production technologies and identified more intensive and extensive production systems for both types of farms, whereby we based our notion of intensive versus extensive dairy production on differences in stocking density and milk yield per cow and year. To be able to compare the productivity levels and productivity developments of the various groups of farms, we developed a group- and chain-linked multilateral productivity index. We also analyzed how technical change, technical efficiency change, and a scale change effect contribute to productivity growth between the years 2000 and 2008. Our results revealed that permanent grassland farms can generally keep up with fodder-crop farms, even in an intensive production setting. However, extensively operating farms, especially those on permanent grassland, significantly lag behind in productivity and productivity change and run the risk of losing ground.

Key words: dairy farm, permanent grassland, total factor productivity, stochastic production frontier

INTRODUCTION

In addition to being an important basis for agricultural production, grasslands provide a variety of essential environmental and social benefits. For instance, grasslands act as a carbon sink (Soussana et al., 2007) and generally ensure a high level of biodiversity because they provide habitats for flora and fauna (Pflimlin and Poux, 2005). The preservation of ground and surface water quality and the provision of an attractive environment for recreational activities and tourism are additional benefits (e.g., Peeters, 2009; Prochnow et al., 2009; Sanderson et al., 2012). Hence, the preservation of permanent grassland is an important topic in the

agricultural conservation policy of the United States and the European Union. The US Grassland Reserve Program was established as part of the 2002 Farm Bill and is one example for these efforts (USDA, 2013). In the European Union, several agri-environmental programs contain grassland protection elements. In addition, plans exist to strengthen legislation that prevents the conversion of grassland to arable land as part of the greening strategy of the 2013 reform of the Common Agricultural Policy (European Commission, 2013). The productive potential of permanent grassland can be exploited only by ruminants and, with some limitations, biogas plants. Hence, dairy farming plays the key role in agricultural production in many grassland regions. In the European heartland, the regions with agricultural production based solely on permanent grassland are generally found in elevated and mountainous areas (e.g., in the surroundings of the Alps and the Massif Central). Dairy farms in these areas often face some natural disadvantages. Most notably, the cultivation of fodder crops, such as corn silage, is not feasible because of comparably high precipitation, lower average annual temperature, and a shorter vegetation period (Meisser and Wyss, 1998; Hein, 2002). The relatively low energy yield per hectare of permanent grassland compared with corn silage illustrates these circumstances effectively. In 2010, the numbers varied between 42 to 67 GJ of NE_L/ha for grass silage and 87 to 110 GJ of NE_L/ha for corn silage for dairy farms in Bavaria (LfL, 2012). Moreover, Thaysen et al. (2010) show that the disadvantage of grassland regarding the energy content of the forage increases over time. Analyzing data from northern Germany between 1985 and 2008, they found an average annual increase in NE_L yield of approximately 1 GJ/ha per year for corn silage compared with only approximately 0.45 GJ/ha per year for grass silage. Nevertheless, grassland dairy farmers have to compete with farmers growing fodder crops on arable land because in most cases they act in the same markets. First, the distances to the more favorable areas are minor. Referring to the zones of ruminant rearing systems in Europe identified by Pflimlin et al. (2005), we find areas labeled as “arable land and livestock regions” and “forage crop regions with temporary grassland plus corn” in close proximity to the permanent grassland regions

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in parts of Austria, Switzerland, southern Germany, and the eastern part of France. Second, the produced milk is not promoted to generate higher farm prices in many cases (for example, as “mountain or hay milk”). However, certain approaches in the marketing of these products can be observed (e.g., the promotion of high-quality cheese in the context of a protected designation of origin). Given the ongoing market liberalization in the dairy sector and the latest farm-price fluctuations, serious concerns exist (e.g., Hopkins, 2011) as to whether dairy farms that operate solely on permanent grassland can compete with farms that use arable land to produce fodder crops.

The objective of this paper was to measure the levels and growth rates of total factor productivity (TFP) of dairy farms in Bavaria and examine whether grassland dairy farms are able to keep up with their fodder-crop counterparts in terms of productive performance. If dairy farming in permanent grassland areas is getting less productive compared with areas with arable land, either agricultural production will be abandoned in these regions or payments directed toward these areas (e.g., less-favored area payments) have to increase over time. MacDonald et al. (2000) discussed some of the undesirable effects agricultural abandonment in mountainous regions can have on environmental parameters (e.g., reductions in biodiversity and landscape quality).

In general, when comparing the productivity of various groups of farms (e.g., organic vs. conventional, intensive vs. extensive, irrigated vs. rain fed, and country A vs. country B) it is important to have information on both the difference in absolute productivity levels and the differences in productivity growth. Only the combination of these components can give a full picture of the present and future performance of one group compared with another. Nevertheless, many studies on the performance of groups of dairy farms concentrate on differences in the TFP growth rates and its decomposition; examples are Brümmer et al. (2002) for the dairy sector in various European Union countries, Newman and Matthews (2006) for specialist versus “other” dairy farms, and more recently, Ma et al. (2012) for dairy farms of various size classes. We followed this strand of the literature and calculated TFP growth. Using the generalized Malmquist productivity index described by Orea (2002), we decomposed productivity growth into technical change, technical efficiency change, and a scale change effect. However, this procedure was not enough to fully answer our research question. Two groups can have equal growth rates, and yet one of them may be much less productive. Likewise, 2 groups can be equally productive at a point in time and still drift apart over time because of very different growth rates. To get a full picture of what is going on

in this sector, we needed to map the TFP levels of both groups over time. To do this, we provided a group- and chain-linked multilateral productivity index based on the indices first introduced by Caves et al. (1982) and refined by Good et al. (1997).

MATERIALS AND METHODS

Empirical Model

To model the multi-input, multi-output technology of agricultural production, we use a parametric output-oriented distance function $D^O(\mathbf{x}, \mathbf{y}, t)$, where D^O is the output-oriented distance function, $\mathbf{x}$ refers to a nonnegative vector of inputs used to produce a nonnegative vector of outputs $\mathbf{y}$ in time period t . See Färe and Primont (1995) for the theoretical derivation of the distance function and its properties. We chose output orientation because we assumed that the farms in our sample were less flexible in the adjustment of their inputs than their outputs. Labor input, which predominantly consists of family workforce, is one example for a rather inflexible input. Breustedt et al. (2011) also noted the low flexibility of the inputs of labor and land in Bavarian dairy farming. Contrariwise, although the aggregated amount of milk is limited by the quota system, the very well-established quota trading system in Germany ensures unrestricted output at the single-farm level. Hence, we argue that farmers decide on a set of short-term inflexible inputs for a given year and aim to obtain the maximum output from those inputs. Our assumptions are in line with Brümmer et al. (2002), Newman and Matthews (2007), and Emvalomatis (2012) who also chose output-orientated distance functions as representations of production technologies for dairy farms in various European Union countries.

We used a flexible translog functional form to limit a priori restrictions on the relationships among inputs and outputs (Morrison Paul et al., 2000; Karagiannis et al., 2004). Hence,

$$\begin{aligned} \ln D_{it}^O(\mathbf{y}, \mathbf{x}, t) = & \alpha_0 + \sum_{m=1}^M \alpha_m \ln y_{mit} + \sum_{k=1}^K \beta_k \ln x_{kit} + \frac{1}{2} \sum_{m=1}^M \sum_{n=1}^M \alpha_{mn} \ln y_{mit} \ln y_{nit} + \\ & \frac{1}{2} \sum_{k=1}^K \sum_{j=1}^K \beta_{kj} \ln x_{kit} \ln x_{jit} + \sum_{m=1}^M \sum_{k=1}^K \delta_{mk} \ln y_{mit} \ln x_{kit} + \\ & \tau_1 t + \frac{1}{2} \tau_2 t^2 + \sum_{m=1}^M \zeta_{mt} t \ln y_{mit} + \sum_{k=1}^K \theta_{kt} t \ln x_{kit}. \end{aligned} \quad [1]$$

In Equation [1], the subscripts $i = 1, 2, \dots, N$ and $t = 1, 2, \dots, T$ denote individual farms and time

periods, respectively; the subscripts $k, j = 1, 2, \dots, K$ indicate various types of inputs; and $m, n = 1, 2, \dots, M$ indicate various types of outputs; $\alpha, \beta, \delta, \tau, \zeta$, and θ are parameters to be estimated.

The parameters of this function must satisfy the symmetry restrictions $\alpha_{mn} = \alpha_{nm}$ and $\beta_{kj} = \beta_{jk}$. We follow Lovell et al. (1994) and Coelli and Perelman (2000) and impose homogeneity of degree 1 in output quantities

$$\left(\sum_{m=1}^M \alpha_m = 1 \text{ and } \sum_{m=1}^M \alpha_{mn} = \sum_{k=1}^K \delta_{mk} = \sum_{m=1}^M \zeta_{mt} = 0 \right) \text{ by}$$

normalizing the function by 1 of the output quantities:

$$\ln \left(\frac{D_{it}^O(\mathbf{y}, \mathbf{x}, t)}{y_{Mit}} \right) = TL(\mathbf{y}^*, \mathbf{x}, t), \text{ with } y_{mit}^* = y_{mit} / y_{Mit}, \quad [2]$$

where TL indicates the translog functional form, and $TL(\mathbf{y}^*, \mathbf{x}, t)$ is the right-hand side of Equation [1] after dividing all the output quantities by y_M . Because the dependent variable $\ln D_{it}^O$ is unobservable, we have to rearrange the distance function for estimation. We add a random error term ν_{it} , and, given that $\ln D_{it}^O \leq 0$, we replace $\ln D_{it}^O$ with $-u_{it}$, such that

$$-\ln y_{Mit} = TL(\mathbf{y}^*, \mathbf{x}, t) + u_{it} + \nu_{it}. \quad [3]$$

Equation [3] is a “stochastic frontier model” (Kumbhakar and Lovell, 2000) and can be estimated by maximum-likelihood methods, given that ν_{it} is a normally distributed random variable $N(0, \sigma_v^2)$ that reflects statistical noise and other stochastic shocks, where σ_v^2 is the variance of the statistical noise term, and u_{it} is a nonnegative random error term $N^+(0, \sigma_u^2)$ that represents inefficiency (Aigner et al., 1977), where σ_u^2 is the variance of the inefficiency term.

Because the aim of our paper is to compare the efficiency and productivity of permanent grassland farms and fodder-crop farms, we split our sample into these 2 groups. We know each farm’s share of permanent grassland in its total utilized land. This information is used to distinguish between the 2 types of farms. However, we have only limited information on potentially heterogeneous production technologies within those 2 groups. To allow for the possibility of unobserved differences in the production technologies, we apply a latent class stochastic frontier model for each of the 2 groups as described in Orea and Kumbhakar (2004), Greene (2005), and Alvarez and del Corral (2010).

The reader might ask why we did not use the latent class model on the complete data set and let the econometric model assign the farms to classes with dif-

ferent (unobserved) production technologies. Alvarez et al. (2012) found that latent class models are better suited to identify heterogeneous technologies than is an a priori split of the sample. However, our research question aims to identify productivity differences between 2 groups of farms, which are not latent to us; rather, we have a clear conception for their separation based on the farms’ shares of permanent grassland. Still, technological homogeneity can be a strong assumption even within those more closely defined subsamples. Hence, we use the latent class model to relax this restriction and allow for unobserved technological heterogeneity.

In the latent class framework, Equation [3] can be rewritten as

$$-\ln y_{Mit} = TL(\mathbf{y}^*, \mathbf{x}, t)|_g + u_{it}|_g + \nu_{it}|_g, \quad [4]$$

where the vertical bar simply indicates that we estimate a specific set of coefficients for each class $g = 1, \dots, G$, and the overall functional relationship remains the same for all the classes. Hence, the heterogeneity in the production technology is captured by a class-specific parameter vector. The true class membership of each farm is unknown to us. It is assumed that a latent relationship between the observations in the sample exists, which translates into G different classes. Following Greene (2005), under the aforementioned distributional assumptions on u_{it} and ν_{it} , the contribution to the conditional likelihood function for each farm i is the product of the likelihood functions in each period:

$$LF_{ig} = \prod_{t=1}^T LF_{itg}, \quad [5]$$

where LF_{itg} is the likelihood function for each observation in each class. To get the unconditional likelihood function for farm i , a weighted average of all its likelihood functions over the G classes is calculated using the G prior probabilities of class membership P_g as weights:

$$LF_i = \sum_{g=1}^G P_g LF_{ig}. \quad [6]$$

The prior probabilities must be specified to have a value between 0 and 1 ($0 \leq P_g \leq 1$) and must sum up to 1 $\left(\sum_{g=1}^G P_g = 1, \forall i \right)$. A simple parameterization of the prior probabilities with 1 class (G) as reference that fulfills these requirements is in the form of a logit model:

$$P_g = \frac{\exp(\rho_g)}{\sum_{g=1}^G \exp(\rho_g)}, \rho_G = 0, \quad [7]$$

where ρ_g are parameters to be estimated. We impose the constraint on the last ρ_g because we only need $G - 1$ parameters to specify the G probabilities. Consequently, the last probability is 1 minus the sum of the first $G - 1$ (Greene, 2003, page 440). Using this formulation, the prior probability of class membership is constant for all the individuals. Based on the concomitant variable model by Dayton and Macready (1988), we incorporate variables on characteristics of each individual i . By these means, the individual specific prior probabilities of class membership can be parameterized by a multinomial logit model:

$$P_{ig} = \frac{\exp(\rho_g \mathbf{z}_i)}{\sum_{g=1}^G \exp(\rho_g \mathbf{z}_i)}, \rho_G = 0. \quad [8]$$

The vector $\mathbf{z}_i$ contains time-invariant farm-specific characteristics, and ρ_g is the respective vector of parameters to be estimated. The parameter in ρ_g denotes the impact of the farm characteristic on the prior probability of belonging to class g . Hence, a positive coefficient in ρ_g implies that a higher value of the respective variable increases the prior probability that a farm i belongs to class g (Wedel and DeSarbo, 2002). If concomitant variables are incorporated in the model to derive individual specific estimates of the prior probabilities, Equation [6] changes accordingly and P_g is replaced by P_{ig} . We derive the log-likelihood function used to estimate the parameters of the production frontier, the composed error term, and the prior class probabilities from the sum of the individual log LF :

$$\log LF = \sum_{i=1}^N \ln LF_i = \sum_{i=1}^N \ln \sum_{g=1}^G P_{ig} \prod_{t=1}^T LF_{itg}. \quad [9]$$

Following Greene (2005), the log-likelihood function [9] is maximized with respect to the parameter set $[\Theta_g]$, where Θ contains all the parameters of the stochastic distance function $[\alpha_g, \beta_g, \delta_g, \tau_g, \zeta_g, \theta_g, \sigma_g^2]$ and the prior class probabilities $[\rho_g]$. The estimated parameters are then used to estimate the conditional posterior probabilities of class membership from

$$P(g|i) = \frac{LF_{ig} P_{ig}}{\sum_{g=1}^G LF_{ig} P_{ig}}. \quad [10]$$

As noted by Orea and Kumbhakar (2004), we can deduce from expression [10] that the posterior class probabilities depend not only on the estimated ρ parameters for the concomitant variables in the logit model [8] but on all the parameters contained in the set $[\Theta_g]$. Hence, if information about possible class characteristics is unavailable, the latent class model still clusters the sample using the goodness of fit of each estimated frontier.

Although we have panel data available, we estimate the posterior class probabilities as $P(g|i)$ instead of $P(g|it)$. This means that the posterior probabilities are the same for each observation of a farm and that the farms are not allowed to switch between the classes over time, contrary to Alvarez and del Corral (2010). We argue that dairy farmers do not decide whether they produce using a more intensive or extensive production technology on a year-to-year basis. Rather, this decision has to be considered as the result of a medium- to long-term strategy because each production technology has particular requirements that are not always easy to adjust every year (e.g., special knowledge by the farmer or specific dairy breeds).

We follow Orea and Kumbhakar (2004) and use the Akaike information criterion (**AIC**) as an indication for the appropriate number of classes. For the econometric implementation of the described model, we use LIM-DEP 10.0 (Greene, 2012; Econometric Software Inc., Plainview, NY).

Production Technology, Technical Efficiency, and Productivity

Based on the stochastic frontier model in Equation [4], we can examine various characteristics of the production technology and derive the technical efficiency and productivity growth of the farms in our sample. The elasticities of the distance functions with respect to inputs and outputs characterize the multi-output production technology in a way similar to the more common parameters of a Cobb-Douglas production function. The first-order elasticities with respect to inputs

$$\varepsilon_{kit} = \frac{\partial \ln D^O}{\partial \ln x_k} = \beta_k + \sum_{j=1}^K \beta_{kj} \ln x_{jit} + \sum_{m=1}^M \delta_{mk} \ln y_{mit} + \theta_{kt} t \quad [11]$$

are, therefore, interpreted as the percentage change in the overall output due to a 1% increase in the respective inputs (Morrison Paul et al., 2000). The sum of these input elasticities (ε) is defined as the scale elasticity (Färe and Primont, 1995):

$$\varepsilon_{it} = \sum_{k=1}^K \varepsilon_{kit}. \quad [12]$$

The first-order elasticities with respect to output are calculated as

$$\varepsilon_{mit} = \frac{\partial \ln D^O}{\partial \ln y_m} = \alpha_m + \sum_{n=1}^M \alpha_{mn} \ln y_{nit} + \sum_{k=1}^K \delta_{mk} \ln x_{kit} + \zeta_{mt} t \quad [13]$$

and reflect the profit maximizing revenue share of the m th output for a given level of inputs (Brümmer et al., 2002). Grosskopf et al. (1995) provide a discussion of the various measures that can be derived from the estimated elasticities on the output side and their economic interpretation.

In contrast to the standard stochastic frontier model, in which 1 homogeneous production technology is assumed, the latent class model can establish several frontiers. In accordance with the estimated a posteriori probability from [10], the farms in the sample are assigned to the identified classes, and their individual technical efficiency score is measured against the respective class technology frontier. Consequently, the technical efficiency scores for individual farms are estimated using the common formula of Jondrow et al. (1982):

$$TE_{it} = \exp[-E(u_{it}|u_{it} + \nu_{it})]. \quad [14]$$

Hence, technical efficiency scores are a measure of the productive homogeneity of the respective class and cannot be used to compare the efficiency of farms across classes. Orea and Kumbhakar (2004) also discuss an alternative approach for the estimation of efficiency scores in a latent class model. It aims to take the uncertainty about class membership into account and calculates a weighted average of the farms' technical efficiency scores as against all possible frontiers:

$$TE_{it}^* = \sum_{g=1}^G P(g|i) TE_{it|g}. \quad [15]$$

Malmquist Index of TFP Growth. To examine productivity growth, we use the well-established generalized Malmquist index of TFP, as suggested by Orea (2002). Details on the derivation of the index and applications to the agricultural sector can be found in Coelli et al. (2005), Newman and Matthews (2006), and Key et al. (2008). The generalized Malmquist index of productivity change between 2 time periods and $s = t + 1$ can be written as

$$\begin{aligned} \ln G_{it, is} = & \frac{1}{2} \left[\frac{\partial \ln D_{is}^O}{\partial t} + \frac{\partial \ln D_{it}^O}{\partial t} \right] + [\ln D_{is}^O - \ln D_{it}^O] \\ & + \frac{1}{2} \sum_{k=1}^K [(\varepsilon_{is} - 1)(\varepsilon_{kis}/\varepsilon_{is}) + (\varepsilon_{it} - 1)(\varepsilon_{kit}/\varepsilon_{it})] \ln \left(\frac{x_{kis}}{x_{kit}} \right). \end{aligned} \quad [16]$$

The index measures how the productivity of an individual farm changes over time and allows for the decomposition of productivity growth in technical change, technical efficiency change, and a scale change effect. Given the estimated parameters of the stochastic distance function, the calculation of the components of productivity change is rather straightforward. Technical change, the first term on the right hand side of Equation [16], includes the partial derivatives of the distance function with respect to time for the periods t and $s = t + 1$, where

$$\frac{\partial \ln D_{it}^O}{\partial t} = \tau_1 + \tau_2 t + \sum_{m=1}^M \zeta_{mt} \ln y_{mit} + \sum_{k=1}^K \theta_{kt} \ln x_{kit}.$$

The second term in Equation [16] measures the change in technical efficiency by the difference in the value of the output distance function from one period to the next. The third term on the right hand side of Equation [16] contains the scale change effect, which is based on the scale elasticity ε_{it} and changes in input use. We observe a positive (negative) contribution to productivity change if $\varepsilon_{it} > 1$ and input usage is expanded (reduced) or if $\varepsilon_{it} < 1$ and input usage is reduced (expanded). In the case of constant returns to scale ($\varepsilon_{it} = 1$) or if input quantities do not change [$\ln(x_{kis}/x_{kit}) = 0$], the scale change effect becomes 0.

Group- and Chain-Linked Multilateral Productivity Index. As noted in the introduction, our analysis goes beyond the examination of the mere growth rates of productivity. To compare the productivity levels of fodder-crop and grassland farms relative to each other, we develop a group- and chain-linked multilateral productivity index. The initial form of this index, as introduced by Caves et al. (1982), provides a measure of the productivity level of all the production units in a cross-section relative to one hypothetical average reference unit. We adapt this index to compare the productivity level of groups that consist of subordinate (micro-level) units over time. This approach combines the indices by Good et al. (1997) and Delgado et al. (2002). The group- and chain-linked multilateral productivity index $\ln P_{it}$ can be written as follows:

$$\begin{aligned}
\ln P_{it} = & \left[\frac{1}{2} \sum_{m=1}^M \left(R_{mit}^h + \overline{R_{mt}^h} \right) \left(\ln y_{mit}^h - \overline{\ln y_{mt}^h} \right) \right. \\
& + \left. \frac{1}{2} \sum_{m=1}^M \left(\overline{R_{mt}^h} + \overline{\overline{R_{mt}^h}} \right) \left(\overline{\ln y_{mt}^h} - \overline{\overline{\ln y_{mt}^h}} \right) \right. \\
& + \left. \frac{1}{2} \sum_{s=2}^T \sum_{m=1}^M \left(\overline{R_{ms}^h} + \overline{\overline{R_{ms-1}^h}} \right) \left(\overline{\ln y_{ms}^h} - \overline{\overline{\ln y_{ms-1}^h}} \right) \right] \\
& - \left[\frac{1}{2} \sum_{k=1}^K \left(C_{kit}^h + \overline{C_{kt}^h} \right) \left(\ln x_{kit}^h - \overline{\ln x_{kt}^h} \right) \right. \\
& + \left. \frac{1}{2} \sum_{k=1}^K \left(\overline{C_{kt}^h} + \overline{\overline{C_{kt}^h}} \right) \left(\overline{\ln x_{kt}^h} - \overline{\overline{\ln x_{kt}^h}} \right) \right. \\
& + \left. \frac{1}{2} \sum_{s=2}^T \sum_{k=1}^K \left(\overline{C_{ks}^h} + \overline{\overline{C_{ks-1}^h}} \right) \left(\overline{\ln x_{ks}^h} - \overline{\overline{\ln x_{ks-1}^h}} \right) \right]. \quad [17]
\end{aligned}$$

In Equation [17], the first term in the first square brackets is a multilateral output index that gives the relative output of the i th unit in each group $h = 1, \dots, H$ against the output of a hypothetical group average unit in each period t . In our application, the superscript $h = 1, \dots, H$ includes all the G latent classes we identify among the permanent grassland and fodder-crop farms. Hence, R_{mit}^h denotes the unit-specific revenue share of the m th output (y_m), and superscript h signifies the group membership of unit i . A single bar over a variable denotes its arithmetic mean for the respective group h (e.g., $\overline{R_m^h} = \frac{1}{N^h} \sum_{i=1}^{N^h} R_{mi}^h \forall h$). The second term in the first square brackets compares the output of the hypothetical group average units themselves against a hypothetical overall average unit. A double bar over a variable indicates the arithmetic mean over the H groups (e.g., $\overline{\overline{R_m^h}} = \frac{1}{H} \sum_{h=1}^H \overline{R_m^h}$). The third term in the first square brackets chain links the output of the hypothetical overall reference units for each period over time and relates it to the overall reference unit in the base year $t = 1$. The second square brackets perform the respective calculations on the input side.

Applying the first-order conditions of cost minimization, we obtain the required input (cost) shares C_k under the assumption of allocative efficiency from the input-side elasticities of the estimated distance functions. Following Chan and Mountain (1983), C_k corresponds to the elasticities corrected by the respective returns to scale measure:

$$C_k = \frac{\partial \ln D^O}{\partial \ln x_k} \bigg/ \sum_{k=1}^K \frac{\partial \ln D^O}{\partial \ln x_k} = \varepsilon_k / \varepsilon. \quad [18]$$

On the output side, we make use of the fact that the revenue shares are observed in the data. This way we can abstain from the assumption of an allocative efficient output mix and use the observed revenue shares for aggregation.

This index provides a measure of the level of productivity for each unit i in each group h and each time period t relative to the overall hypothetical reference unit in the base year $t = 1$. This way, the “path of comparison” (Good et al., 1997, page 11) is still well defined, and transitivity is maintained. Furthermore, we obtain information on the variability of TFP within and between the H groups and how this variability develops over time. In this application, we are mainly interested in productivity gaps between the identified groups of dairy farms. The multilateral Törnqvist index does not allow for the measurement of the effects of nonconstant returns to scale or technical inefficiency to explain productivity dispersion. We note that these restrictions are necessary for the calculation of the relative productivity measures across distinct production technologies.

Data

We use an unbalanced panel data set taken from farm bookkeeping records, which serves as a basis for the European Commission’s Farm Accountancy Data Network. The farm-level data set includes 9,482 observations of 1,142 dairy farms observed over the years 2000 to 2008 in the Federal state of Bavaria in southern Germany. All the farms are specialized dairy farms, with more than 66% of the farms’ total revenues coming from dairy production. The observations are evenly spread over the period under consideration with 8.3 observations per farm, on average. Overall, 958 farms are identified as fodder-crop farms, and 184 farms are permanent grassland farms. The farms considered to be grassland farms operate with 100% permanent grassland during the entire period. Although fodder-crop farms may operate partly on permanent grassland, it never exceeds 90% of their total farm land. The average share of permanent grassland in the fodder-crop group is 45%. All the monetary figures from accounting data are deflated using relevant price indices from the German Federal Bureau of Statistics. For the fodder-crop farms, we aggregate the outputs into 2 categories: milk and other output. Milk is equal to revenues from

Table 1. Summary statistics of main variables for fodder-crop and grassland farms

Item	Fodder crop (958 farms; 7,999 observations)				Grassland (184 farms; 1,483 observations)			
	Mean	Maximum	Minimum	SD	Mean	Maximum	Minimum	SD
Labor, fte ¹	1.57	3.94	0.40	0.46	1.49	2.97	0.35	0.35
Land, ha	46.2	318.3	9.4	26.0	31.2	81.4	12.3	11.9
Intermediate inputs, €	54,171	247,089	6,145	29,462	28,862	101,581	5,349	12,792
Capital, €	216,589	106,3470	14,767	129,886	152,885	398,067	21,395	81,251
Milk output, €	75,950	310,611	9,122	39,307	68,623	204,891	21,301	24,072
Other output, €	31,852	239,780	2,276	17,863	1.54	3.06	0.70	0.35
Cattle LU/ha of forage land ²	2.36	5.64	0.85	0.58	5,947	8,258	3,365	915
Yearly milk yield, kg/cow	6,079	9,162	2,253	1,001	1.49	2.97	0.35	0.35

¹fte = full-time equivalent.²LU = livestock unit.

raw milk and milk products. This allows accounting for quality differences because the price that the individual farmer receives from the processor varies depending on the fat and protein content in the milk [see Reinhard et al. (1999) and Emvalomatis (2012)]. The variable other output contains revenues from beef, crops, and other commodities. We also tried a multi-output specification for the grassland farms. However, the estimated distance function encountered substantial monotonicity problems. This is not surprising, given that grassland farms are highly specialized. Their average share of dairy production on the total output is 92.6%, with 80.2% as a minimum. Therefore, as common practice in the case of highly specialized dairy farms (e.g., Abdulai and Tietje, 2007), we estimate a production frontier that is the single-output special case of an output distance function. For both groups of farms, we aggregate the inputs used into 4 categories (labor, land, intermediate inputs, and capital). Table 1 summarizes the descriptive statistics for the main variables of the stochastic frontier model.

Labor includes family and hired labor in full-time equivalents. Land measures the total cultivated land in hectares. Thus, differences in land quality are omitted. We tackle this issue by introducing regional dummies for various agricultural production areas, as defined by the Bavarian Agricultural Research Institute (LfL, 2009). Intermediate inputs include all the expenses for forage and crop production (e.g., seed, fertilizer, pesticides, and contractors), for animal production (e.g., veterinary and concentrates) and for water, energy, fuel, and other expenses linked to production. Capital includes the end-of-year value of livestock, buildings, technical facilities, and machinery related to agricultural production. Similar input specifications for dairy farms can be found in Kumbhakar and Heshmati (1995), Brümmer et al. (2002), and Newman and Matthews (2006). In addition to the variables of the distance function, we use the farm average value of the variables cattle live-

stock unit per hectare of forage land and yearly milk yield per cow as concomitant variables in the model for the prior probabilities of the latent classes. These variables most commonly characterize intensive or extensive dairy production systems (Müller-Lindenlauf et al., 2010; Nehring et al., 2011).

RESULTS

Econometric Estimates of the Production Technology

Estimation results based on 7,999 (1,483) observations for the group of fodder-crop (grassland) farms are presented in the online supplements to conserve space (Supplementary Tables S1 and S2; <http://dx.doi.org/10.3168/jds.2013-7825>). In the case of fodder-crop farms, 87% of the estimated parameters are statistically significantly different from zero at the 5% level (52% for the grassland farms). For the group of fodder-crop farms, the AIC indicates that a model with 2 classes (AIC = -1.245) is preferred over a model with 1 class (AIC = -0.740). Attempts to estimate a model with 3 or more classes failed to achieve convergence. For the group of grassland farms, the AIC also supports a model with 2 classes against a model with 1 class (AIC of -1.020 and -1.412, respectively). However, for this group, a model with 3 classes and a slightly lower AIC can be estimated, but with very poor results. In particular, the additional class is very small and the distance function coefficients are insignificant with extreme standard errors. In accordance with Greene (2005), who reported a similar case, we prefer a model with 2 classes in both groups. The coefficients for the concomitant variables in the latent class model are shown in Table 2. The positive signs indicate that a higher value of the variables milk yield per cow per year and cattle livestock unit per hectare of forage land increases the probability of a farm to belong to class 1

in both groups. For the size of the effect and a more detailed interpretation, the marginal effects of the variables on the prior probability have to be calculated. However, the signs of the marginal effects depend on the signs of the coefficients. Because we are not interested in the size of the marginal effect, we check only the estimated coefficients. Using a likelihood ratio test, we examine their statistical significance. For both groups, we find that the variables provide additional information to classify the sample (Table 2). However, it is important to note that the assignment of farms to the classes is only slightly affected by the specification of the prior probability function. Including the concomitant variables (cattle livestock unit per hectare of forage land and yearly milk yield per cow) in the probability function (see Equation [8]), we find that only 27 out of the 958 fodder-crop farms (6 out of the 184 grassland farms) were assigned to a different class compared with the simpler model with no concomitant variables included (Equation [7]). Hence, we argue that the major effect for sorting the farms into the classes can be attributed to differences in the distance functions' coefficients, representing distinct production technologies.

Taking the results from Table 2 in combination with the key properties of the various classes into account (Table 3), we conclude that the degree of intensification is at least 1 major distinguishing characteristic of the 2 identified classes in each group. Hence, we refer to the classes as intensive and extensive, but we are fully aware that other interpretations of these results might exist. As depicted in Table 3, in both groups (henceforth referred to as **PGL-I** and **PGL-E** for intensive and extensive permanent grassland, respectively, and **FC-I** and **FC-E** for the respective fodder-crop farms), the so-called intensive farms produce relatively more milk, on average, and use an almost equal work force

and area under cultivation. These farms have a higher stocking rate and larger dairy herds, use more intermediate inputs, achieve higher milk yields per cow, and have expanded their production faster than the extensive farms. For the PGL farms, the difference in the latter is most striking. The PGL-E farms achieved a yearly growth rate of approximately 1.17%, but the PGL-I farms increased their milk output more than 2.6% per year during the observed period. The FC-I (FC-E) farms expanded their milk production at a rate of 2.9% (2.39%) per year. Hence, the group of PGL-E farms lagged behind the other 3 groups regarding the expansion of production. The FC farms showed a higher stocking rate compared with PGL farms. This finding is attributed to the higher forage yields from arable land compared with permanent grassland.

Surprisingly and despite the higher milk yields per cow in the intensive classes in both groups, we found higher costs for veterinary services per cow in the extensive classes. Likewise, the costs of concentrate per cow were larger for PGL-E farms compared with intensive ones. Both observations may be explained by better management skills in the intensive classes. This argument is supported by observed educational differences. The highest percentage of farm managers with no agricultural education was found in the PGL-E class (14.1%), and the lowest was found in the FC-I (6.7%) class. Contrariwise, about twice as many farmers (32%) in the FC-I class received higher agricultural education as those in the PGL-E class (16.5%). For the FC-E (23.2%) and the PGL-I (20.7%) class, the respective figures lay somewhere in between.

To examine the estimated representations of the production technologies for the 4 identified classes, we focused on the first-order production and scale elasticities and the estimated efficiency scores. We calculated the first-order elasticities with respect to inputs and

Table 2. Parameters of the latent class prior probability function

Item	Fodder crop		Grassland	
	Intensive	Extensive	Intensive	Extensive
	Coefficient (SE)		Coefficient (SE)	
Parameter				
Constant (ρ_0)	-7.563 (0.677) ^a	—	-7.090 (1.662) ^a	—
Yearly milk yield (ρ_1), kg/cow	1.183 (0.178) ^a	—	2.801 (0.611) ^a	—
Cattle LU/ha of forage land (ρ_2) ¹	0.080 (0.009) ^a	—	0.059 (0.020) ^a	—
LR test ²	LR statistic		LR statistic	
$H_0: \rho_1 = \rho_2 = 0$	186.7 ^a		35.3 ^a	

^aStatistical significance on the 1% level.

¹LU = livestock unit.

² H_0 = null hypothesis.

Table 3. Characteristics of identified production systems (class averages)

Item	Fodder crop		Grassland	
	Intensive	Extensive	Intensive	Extensive
Farms, no.	491	467	116	68
Observations, no.	4,100	3,899	951	532
Labor, fte ¹	1.60	1.54	1.49	1.48
Land, ha	46.9	45.5	31.4	30.9
Intermediate inputs, €	58,602	49,510	31,116	24,833
Cows	41	32	30	22
Milk production, 1,000 kg/yr	265.1	185.3	180.9	125.7
Concentrate/cow, €	312.3	277.2	259.7	274.1
Cattle LU/ha of forage land ²	2.54	2.18	1.64	1.37
Milk yield, kg/cow per year	6,432	5,708	6,087	5,693
Veterinary cost/cow, €	90.3	99.6	76.0	96.8
Average growth rate milk yield, %/yr	1.80	1.87	1.61	1.41
Average growth rate milk production, %/yr	2.90	2.39	2.61	1.17
No agricultural education, %	6.7	8.8	9.8	14.1
Basic agricultural education, %	61.3	68.0	69.5	69.4
Higher agricultural education, %	32.0	23.2	20.7	16.5
Farmer age, yr	46.7	48.2	46.9	47.3

¹fte = full-time equivalent.²LU = livestock unit.

outputs at each data point and presented their average values for each class in Table 4.

In all the classes, the average elasticities showed the expected signs. As a general pattern, intermediate inputs had the highest average output elasticity, followed by land, labor, and capital. For the FC-I class, the average elasticity of the intermediate inputs with respect to output equaled 0.543. That is, a 1% increase of this input resulted in a 0.543% increase in aggregate output. Comparing the elasticities between the 2 groups of farms, we found output to be relatively more responsive to land and labor for the PGL farms. On the other hand, intermediate inputs and capital had a greater effect on output for the FC farms. These findings show the relative importance of the input land, in particular for the PGL dairy farms. This reflects

the more pronounced necessity of pure grassland-based farms for additional land to increase their output. In contrast, FC farms have more alternative means of output expansion because arable land is more versatile. The elasticities on the output side reflect the high share of milk output in the total production of both fodder-crop classes. We checked whether the estimated parametric representations of the production technologies satisfied the monotonicity condition at each data point. We found only few violations, primarily for the input capital (Supplementary Table S3; <http://dx.doi.org/10.3168/jds.2013-7825>). However, the percentage of violations was still low, and we expect no substantial consistency problems regarding monotonicity.

Returns to scale slightly decreased for all the classes at their sample mean. Considering the relatively mod-

Table 4. Average elasticities for the 4 identified classes¹

Item	Fodder crop ²		Grassland	
	Intensive	Extensive	Intensive	Extensive
Labor	0.104 (0.047) ^a	0.155 (0.066) ^b	0.122 (0.027) ^c	0.203 (0.080) ^d
Land	0.172 (0.077) ^a	0.177 (0.112) ^a	0.284 (0.099) ^c	0.313 (0.096) ^d
Intermediate inputs	0.543 (0.044) ^a	0.523 (0.062) ^b	0.421 (0.048) ^c	0.370 (0.054) ^d
Capital	0.121 (0.048) ^a	0.136 (0.077) ^b	0.080 (0.067) ^c	0.089 (0.094) ^c
Scale	0.940 (0.037) ^a	0.991 (0.091) ^b	0.907 (0.054) ^c	0.976 (0.083) ^d
Milk output	−0.721 (0.055) ^a	−0.715 (0.052) ^b	—	—
Other output	−0.279 (0.055) ^a	−0.285 (0.052) ^b	—	—

^{a-d}Means within a row with different superscript letters differ significantly on the 1% level based on a Welch test.

¹Standard deviations in parentheses.

²The coefficients of the output distance function were multiplied by −1 to facilitate the comparison with the production frontier. For that reason, we found positive (negative) signs for the elasticities on the input (output) side.

est size of the dairy herds in our sample this result was surprising at first sight. However, it is not an uncommon finding in similar research: see, for example, Emvalomatis (2012) for dairy farms in Germany, Abdulai and Tietje (2007) for northern German dairy farms, and Barnes (2008) for dairy farms in Scotland. Moreover, Alvarez and Arias (2003) showed that diseconomies of size can occur if farms increase their size but not managerial abilities. We checked the distributions of the scale elasticities and found that they were more widely distributed in the extensive classes, which showed a considerable number of observations with decreasing and increasing returns to scale. The distributions for the intensive classes were narrower, with only a small number of observations with returns to scale greater than 1.

Regarding the coefficients associated with time (all θ and τ in Supplementary Tables S1 and S2; <http://dx.doi.org/10.3168/jds.2013-7825>), we found non-neutral technical change in all 4 identified technologies. With only 1 exception (parameter θ_{3t} in the FC-E class), technical change saves labor and capital and uses land and intermediate inputs (see Morrison Paul et al., 2000 for details on the interpretation of the coefficients of non-neutral technical change). However, the coefficients varied in value and significance across all the classes. For instance, technical change for the PGL-I class was almost exclusively disembodied, but we did not find significant disembodied technical change for the extensive class. This implies that the contribution of technical change to TFP for the PGL-E class stemmed mainly from changes in the marginal productivities of single inputs over time. We tested whether the presence of non-neutral technical change could be rejected for the class of PGL-I farms. The Wald statistic for the hypothesis $H_0: \theta_{1t} = \theta_{2t} = \theta_{3t} = \theta_{4t} = 0$ is equal to $\chi^2(4) = 3.913 < \chi^2_{0.95} = 9.487$. Hence, the coefficients for non-neutral technical change are not significantly different from zero. Because we did not face restrictions in degrees of freedom, we still kept the respective variables in the model to preserve a model specification consistent with the other classes.

Technical Efficiency

As noted above, the technical efficiency scores we report were measured against the most likely frontier for each farm. Hence, this approach did not take the uncertainty of class membership into account and is in the line of thought by Greene (2007), who favored the parameter associated with the most likely class as the best estimator for a “unit specific” parameter in a latent class model. However, the uncertainty in the

class assignment of the farms was very low. This was reflected by average a posteriori probabilities of class membership of 0.983 for the FC farms and 0.982 for PGL farms. Consequently, we found almost identical results if the technical efficiency scores were calculated as a weighted average using Equation [15].

The average technical efficiency scores for the intensive and extensive FC classes were 0.977 and 0.917, respectively. The average values for the PGL classes were 0.954 (intensive) and 0.937 (extensive). Hence, the farms in the intensive classes were, on average, more efficient and, as a more homogeneous class, closer to their own frontier for both groups. The cumulative distributions of efficiency scores in Figure 1 show that most of the farms were highly efficient in all the classes. However, especially in the extensive classes, inefficient farms existed, which dragged down the class' average efficiency. For the FC-E and the PGL-E classes, we found that 31.1 and 15.4% of the farms exhibited efficiency scores below 0.9, respectively. In contrast, only 2.6% of the PGL-I and none of the FC-I farms showed efficiency scores below 0.9. Cabrera et al. (2010) also identified a positive relationship between intensification and technical efficiency for dairy farms by using an inefficiency effects model. Alvarez and del Corral (2010) reported similar results, and they ascribed these findings to the assumption that intensive systems might be easier to manage and farmers are less prone to make mistakes. The shape of the distributions in Figure 1 supports this interpretation. Differences in the managerial quality could be another interpretation. This is supported by

Figure 1. Empirical cumulative distributions of technical efficiency scores for the identified intensive and extensive classes in the fodder-crop (FC) and permanent grassland (PGL) groups. The vertical grid line indicates a technical efficiency score of 0.9.

the aforementioned differences in veterinary costs and the farmers' agricultural education.

Putting the estimated efficiency scores for the 4 groups in context with the rich literature on dairy farm efficiency, we found the class-average scores to be relatively high [see Bravo-Ureta et al. (2007) and Moreira López and Bravo-Ureta (2009)]. We attributed this finding mainly to the methodological design of the study, which mitigated the confusion of technological heterogeneity with technical inefficiency (see also Alvarez and del Corral, 2010).

Productivity Analysis

The results for the calculation of the Malmquist index of TFP change and its decomposition are summarized in Table 5. Technical change accounted for the major part of TFP change in all the classes. Except for the extensive PGL farms, the effect of technical efficiency change was only very small. We found negative scale change effects for both the FC and the PGL-E farms and a positive effect for the PGL-I farms. Again, except for the FC-E farms, the impact of the scale effect on TFP growth was negligible.

Table 5 also shows year-to-year TFP changes for the 4 classes and the cumulative growth from 2000 to 2008. We observe steady TFP growth for the FC-I farms, with slightly increased rates after 2004. The class of FC-E farms exhibited rather low TFP growth in the first years, but the growth rates increased from 2004 on and caught up to those of the FC-I class. The PGL-I

class showed the highest growth rates in the first years, but the rates decreased over time; we even found a decrease in productivity from year 2007 to 2008. The average TFP change rates for the PGL-E farms were unsteady. In the FC group, the intensive (extensive) farms reached an average annual rate of 1.24% (0.97%). The PGL farms improved their productivity, on average, at an annual change rate of 1.18% for the intensive class but only 0.53% for the extensive class. These rates resulted in a cumulative productivity growth during the observed period of 9.9 and 7.7%, respectively, for the intensive and extensive FC classes and 9.4 and 4.2% for the respective PGL classes.

Turning now to the results of the multilateral Törnqvist index, we checked for differences in the productivity levels of the 4 identified classes. Figure 2 summarizes the main results. Each line represents the percentage deviation of the 4 groups' hypothetical reference farm from the productivity of the overall reference farm in the base year and its evolution over time. For example, the FC-I class reached an average productivity level of 22.1% in the year 2007. This means that the average farm in the FC-I class produced 22.1% more output using a given amount of inputs in 2007 than the overall average reference farm in the year 2000.

Starting in the base year 2000, we found the FC-I class to be 12.7% more productive than the overall reference farm. The PGL-I class also lay well above the overall reference (7.6%). In contrast, the extensive classes consequently underperformed (−12.8 and −7.4%). The ranking of the 4 groups did not change

Table 5. Malmquist index of total factor productivity (TFP) change for the 4 identified classes

Item ¹	Fodder crop				Grassland			
	Intensive		Extensive		Intensive		Extensive	
	ΔTFP ²	Cumul. ³	ΔTFP	Cumul.	ΔTFP	Cumul.	ΔTFP	Cumul.
Year		0.00		0.00		0.00		0.00
2000/2001	1.06	1.06	0.62	0.62	2.60	2.60	0.78	0.78
2001/2002	0.90	1.97	0.34	0.97	1.81	4.40	1.21	1.99
2002/2003	1.16	3.13	0.46	1.42	1.21	5.61	0.45	2.44
2003/2004	0.99	4.12	0.67	2.10	1.59	7.20	0.98	3.42
2004/2005	1.42	5.54	1.33	3.43	1.09	8.29	−0.24	3.19
2005/2006	1.41	6.95	1.73	5.16	1.05	9.34	0.83	4.01
2006/2007	1.58	8.53	1.74	6.90	0.55	9.89	1.26	5.28
2007/2008	1.37	9.90	0.83	7.73	−0.48	9.41	−1.06	4.22
Average annual change rate (%)								
TFPC	1.24		0.97		1.18		0.53	
TC	1.27		1.10		1.18		0.66	
TEC	−0.01		−0.02		−0.03		−0.13	
SC	−0.03		−0.12		0.03		−0.01	

¹TFPC = total factor productivity change; TC = technical change; TEC = technical efficiency; SC = scale change.

²ΔTFP = class average percentage TFP change between the indicated years.

³Cumul. = cumulative percentage TFP change.

Figure 2. Percentage deviation of the class reference unit's total factor productivity (TFP) from the overall average TFP in the base year 2000. Intensive and extensive classes in the fodder-crop (FC) and permanent grassland (PGL) groups in years 2000 to 2008 are shown. Values are indicated for the 4 classes in the years 2000, 2007, and 2008.

during the observed period. However, the differences between the intensive and extensive classes increased over time. Although the difference between the intensive and extensive FC (PGL) farms was 20.1% (20.4%) in 2000, it was 22.2% (23.9%) in 2008.

DISCUSSION

The key results of the study can be summarized as follows. With respect to their technology's own frontier, most farmers in all the classes were highly technically efficient. However, we found substantial differences by comparing the productivity of the 4 classes. The intensive classes in both groups of farms were more productive and were also able to increase their productivity to a greater extent over the observed period. Technical progress was by far the most important component of TFP growth for all the classes. Our calculations of the multilateral Törnqvist index revealed that both the FC classes were more productive than their PGL counterparts. However, our distinction between intensive and extensive classes shows that highly productive grassland farms exist that can keep up with the fodder-crop farms and that those farms are predominantly found in the more intensive class of farms. The more substantial productivity gap existed between the intensive and extensive classes, and this gap widened because of

the higher productivity growth rates in the intensive classes. To some extent, this finding questions payments, particularly targeted to grassland farms. For a note on the comparability of the Malmquist index of TFP growth and the multilateral Törnqvist, see Kellermann (2014).

Some evidence exists that being in the group of intensive or extensive farms is, at least to some extent, not an intentional decision made by the farmer but is also related to his/her management skills. In both of the intensive groups, farmers were, on average, better educated and had to spend less on veterinary services. The management skills were also reflected in the technical efficiency scores. The farmers in the intensive classes produced very close to their frontier. This indicates hardly any errors in management. The abolishment of the milk quota system in 2015 might change the situation to some extent. Production controls usually limit technical change and one could argue that this helped permanent grassland farmers to keep up with their advantaged counterparts. Given that the PGL-E class had the lowest productivity and productivity growth rates, this suggests a shift toward more intensive production technologies in permanent grassland regions. This could occur either because extensive farms are more prone to leave the market or because farmers manage to steadily increase the intensity of their production.

However, regarding the aforementioned additional benefits (biodiversity, carbon storage, and landscape) of cultivated permanent grassland, we have to stress that these benefits predominantly apply to a more extensive form of cultivation (Poetsch, 2007). Müller-Lindenlauf et al. (2010), who identified the same 4 groups of dairy farms (intensive vs. extensive; grassland vs. fodder crop), noted that intensive farm types tended to be advantageous in global categories, such as climate impact and land demand, and the low-input farm types had advantages in local categories, such as the emission of ammonia, animal welfare, and milk quality. Therefore, on the one hand, stimulation of further intensification could help to improve productivity in the dairy sector, especially in permanent grassland regions. On the other hand, exactly where we identified the greatest potential for productivity gains, further intensification could be counterproductive for the provision of local external benefits.

Our analysis stresses the importance of looking at both the levels of productivity and productivity changes when comparing various groups. To do so, we provided a group- and chain-linked multilateral productivity index. We considered this index to be particularly useful for empirical applications that combine inter- and intragroup comparisons over time. Based on firm-level data, it can provide a convenient measure of the productivity variation among farms in a group and between the groups over time. A natural application would be the comparisons of industries in various countries or regions. Other examples are conventional versus organic production and large versus small operations. However, in this context, we have to point toward the weighting adjustments that could become necessary to obtain adequate results and to take the potential differences between aggregated productivity and the productivity of the average production unit into account. For a note on alternative weights in the multilateral index, see Kellermann (2014).

The research of Kumbhakar et al. (2009), Mayen et al. (2010), and Moreira and Bravo-Ureta (2010) is closely related to, but to some extent different from our framework. Mayen et al. (2010) used a propensity score matching approach to compare the efficiency and productivity of organic and conventional dairy farms in the United States. Hence, they directly compared the efficiency and productivity of pairs of conventional and organic farms, which were completely identical except for their technology under ideal circumstances. This has 2 advantages: first, it accounts for a potential self-selection bias from endogenous technology choice; second, the measured differences are directly and solely attributable to the difference in technology. However, the problem we face here is somewhat different. In our

case, technology was not endogenous but rather was given by the exogenous location of the farm. Hence, a self-selection problem was not present. Moreover, because our question was whether grassland farms can compete, we were not interested in the differences in productivity attributable only to technology, but rather in the overall difference. For example, grassland farms in mountainous areas may be smaller than their counterparts because access to land is limited, given the topology. Observed differences in efficiency and productivity might originate from differences in technology or differences in size. The additional scope for diversification might be an additional advantage for the group of fodder-crop farms. Kumbhakar et al. (2009) compared the performance of organic and conventional dairy farms in Finland. They accounted for a potential self-selection bias by jointly estimating production technologies and technology choice decisions. Subsequently, they calculated predicted outputs for each farm, using the observed input mix and estimated parameters of the alternative production technologies. They interpreted the gap between each farm's predicted outputs from various production technologies given observed inputs as the difference in productivity between the respective technologies. Moreira and Bravo-Ureta (2010) analyzed the technical efficiency of dairy farms in 3 South American countries, whereby they used the metafrontier concept described in O'Donnell et al. (2008) to compare efficiency scores across various technologies. This involves the estimation of a specific frontier for each technology group and a metafrontier that envelops all the group frontiers. The efficiency of each farm is then measured against its own group frontier, and the group frontiers are subsequently compared with the metafrontier. The approaches used by Kumbhakar et al. (2009) and Moreira and Bravo-Ureta (2010) measured the potential productivity of a farm if it had access to a different technology but kept its initial input mix fixed. However, it is likely that switching to an alternative production technology also implies changes in the input mix.

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