Comparing productivity growth in conventional and grassland dairy farms.

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Abstract

This paper analyzes technical efficiency and productivity growth of dairy farms in southern Germany. We compare the performance of farms operating on permanent grassland and conventional farms using fodder crops from arable land. Using a latent class stochastic frontier model, intensive and extensive production systems are identified for both types of farms. We estimate stochastic output distance functions to represent the production technology. TFP change is calculated and decomposed using a generalized Malmquist productivity index. Our results show that grassland farms can in general keep up with conventional farms. The productivity on intensive (extensive) grassland dairy farms grew by 1.15% (0.93%) per year, compared to 1.19% (intensive) and 1.0% (extensive) on conventional farms.

Keywords: productivity, dairy farming, stochastic frontier analysis

1. Introduction

About one third of the agricultural area in the European Union is under permanent grassland (EU COMMISSION 2008). Besides being an important basis for agricultural production, grasslands provide a variety of essential environmental benefits such as carbon storage, habitat function, preservation of ground and surface water quality and provision of an attractive environment for recreational activities. The productive potential of permanent grassland can only be exploited by ruminants and with considerable limitations by biogas plants. In many grassland regions dairy farming plays the most important role in agricultural production. However, permanent grassland dairy farms often face relatively high production costs due to natural disadvantages. In addition, they are on average often smaller than their counterparts in favorable areas and therefore can exploit economies of scale to a smaller extent. Given the ongoing market liberalization in the dairy sector and the latest farm-price fluctuations, serious concerns exist whether dairy farms operating solely on permanent grassland (PGL) can compete with farms using arable land to produce fodder crops (e.g. silage maize), specified herein as conventional farms (CON).

The aim of this paper is to examine if grassland dairy farms in Bavaria are able to keep up with conventional farms. This is important because alternatives to dairy farming are scarce in these regions. If dairy farming on permanent grassland becomes less and less competitive compared to farms with arable land, agricultural production will be abandoned in these regions. To answer this question we analyze the efficiency and productivity of both farming systems. To do so, we estimate separate parametric translog output distance functions for each group, using a stochastic frontier approach. To account for different degrees of intensification within the two separated groups, we follow ALVAREZ and DEL CORRAL (2010) and apply a latent class model (LCM). In order to examine how productivity developed between 2000 and 2008 and to identify the contributing factors we construct a generalized Malmquist productivity index (OREA 2002) for both groups of farms.

The rest of the study is organized as follows. Section 2 describes the methodology and section 3 the data. In section 4 we present the empirical results. Concluding remarks follow in the last section.

2. Methodology

In order to model the multi-input multi-output technology of agricultural production we use a parametric output-oriented distance function $D^O(\boldsymbol{x}, \boldsymbol{y}, t)$, where $\boldsymbol{x} = (x_1, x_2, \dots, x_k) \in R_+^K$ refers to a nonnegative vector of inputs used to produce a nonnegative vector of outputs $\boldsymbol{y} = (y_1, y_2, \dots, y_m) \in R_+^M$ given an exogenous time trend $t = 1,2, \dots, T$. We use a flexible translog functional form, in order to limit a priori restrictions on the relationships among inputs and outputs (e.g. MORRISON PAUL et al. 2000; BRÜMMER et al. 2002; NEWMAN and MATTHEWS 2006). Hence,

$$\ln D_{it}^{O}(\boldsymbol{y},\boldsymbol{x},t) = \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mit} + \sum_{k=1}^{K} \beta_k \ln x_{kit} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn} \ln y_{mit} \ln y_{nit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{j=1}^{K} \beta_{kj} \ln x_{kit} \ln x_{jit} + \sum_{m=1}^{M}\sum_{k=1}^{K} \delta_{mk} \ln y_{mit} \ln x_{kit} + \varepsilon_1 t + \frac{1}{2}\varepsilon_2 t^2 + \sum_{m=1}^{M} \zeta_{mt}\, t \ln y_{mit} + \sum_{k=1}^{K} \theta_{kt}\, t \ln x_{kit} \quad (1)$$

The parameters of this function must satisfy the symmetry restrictions $\alpha_{mn} = \alpha_{nm}$ and $\beta_{kj} = \beta_{jk}$. In addition, following COELLI and PERELMAN (2000) homogeneity of degree one in output quantities ($\sum_{m=1}^{M} \alpha_m = 1$ and $\sum_{m=1}^{M} \alpha_{mn} = \sum_{k=1}^{K} \delta_{mk} = \sum_{m=1}^{M} \zeta_{mt} = 0$) is imposed by normalizing the function by an arbitrarily chosen output quantity:

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

where TL indicates translog, and $TL\,(\boldsymbol{y}^{*},\boldsymbol{x},t)$ is the right hand side of (1) after dividing all output quantities by y_2. Because the dependent variable $\ln D_{it}^{O}$ is unobservable, we have to rearrange the distance function for estimation in a stochastic frontier framework. We add a random error term v_{it} and given that $\ln D_{it}^{O} \leq 0$, we replace $\ln D_{it}^{O}$ with $-u_{it}$ such that,

$$-\ln y_{2it} = TL\,(\boldsymbol{y}^{*},\boldsymbol{x},t) + u_{it} + v_{it} \quad (3)$$

Equation (3) can be estimated by maximum-likelihood methods, given that v_{it} is normally distributed statistical noise $(0, \sigma_v^2)$, and u_{it} is a non-negative random error term $N^{+}(0, \sigma_u^2)$ representing inefficiency.

Since the aim of the paper is to compare the efficiency and productivity of permanent grassland (PGL) farms with conventional farms (CON), we split our sample into these two groups. To account for heterogeneous production technologies within these two groups we apply a latent class stochastic frontier model for each of the two groups as described in detail in OREA and KUMBHAKAR (2004) and GREENE (2005). In a similar attempt ALVAREZ and DEL CORRAL (2010) identify extensive and intensive dairy production systems. In the latent class framework equation (3) can be rewritten as:

$$-\ln y_{2it} = TL\,(\boldsymbol{y}^{*},\boldsymbol{x},t)|_g + u_{it}|_g + v_{it}|_g \quad (4)$$

where the vertical bar indicates that we estimate different models for each class $g = 1, \dots, G$, while the overall functional relationship remains the same for all classes. Hence, the heterogeneity in the production technology is captured by a class specific parameter vector. The main benefit of a latent class model is that it allows us to divide the groups in different classes and still estimate the parameters of the production frontiers in one step. 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, translating into G different classes. Following GREENE (2005), under the aforementioned distributional assumptions on u_{it} and v_{it} (the standard normal-half normal model) the contribution to the conditional (on class g) likelihood function (LF) for each farm i is:

$$LF_{ig} = \prod_{t=1}^{T} LF_{itg} \qquad (5)$$

where LF_{itg} is the likelihood function for each observation in each group (see e.g. ALVAREZ and DEL CORRAL 2010, GREENE 2005 or KUMBHAKAR and LOVELL 2000). To get the unconditional LF for farm i, a weighted average of all its LF over the g classes is calculated, using the g prior probabilities of class membership as weights:

$$LF_i = \sum_{g=1}^{G} P_{ig}\, LF_{ig} \qquad (6)$$

The prior probabilities of membership to a class can be parameterized by a multinomial logit model:

$$P_{ig} = \frac{\exp(\rho_g z_i)}{\sum_{g=1}^{G} \exp(\rho_g z_i)} \qquad (7)$$

This model (7) allows for sharpening the prior probabilities by time invariant farm specific characteristics (the vector z_i). 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:

$$\log LF = \sum_{i=1}^{N} \log LF_i = \sum_{i=1}^{N} \log \sum_{g=1}^{G} P_{ig} \prod_{t=1}^{T} LF_{itg} \qquad (8)$$

GREENE (2005) suggests some conventional methods to maximize the log likelihood function (8) with respect to the parameter set $[\Theta_g]$, where Θ contains all parameters of the stochastic distance function $[\alpha_g, \beta_g, \delta_g, \varepsilon_g, \zeta_g, \theta_g, \sigma_g^2]$ and the prior class probabilities $[\rho_g]$. The estimated parameters are then used to estimate the conditional posterior probabilities of class membership from:

$$P(g|i) = \frac{LF_{ig}\, P_{ig}}{\sum_{g=1}^{G} LF_{ig}\, P_{ig}} \qquad (9)$$

As pointed out by OREA and KUMBHAKAR (2004) we can deduce from this expression (9) that the posterior class probabilities depend not only on the estimated ρ parameters from the logit model (7), but on all parameters contained in the set $[\Theta_g]$. Hence, if we don't have information about possible class determinants, a latent class model can still cluster the sample using the goodness of fit of each estimated frontier. Since 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 contrary to ALVAREZ and DEL CORRAL (2010) the farms are not allowed to switch between the different classes over time.

To observe how productivity developed over the period 2000 to 2008 for the different production technologies the generalized Malmquist productivity index, suggested by Orea

(2002) is utilized[1]. It allows for the measurement and decomposition of productivity growth based on estimated parameters of an output-oriented translog distance function. The generalized Malmquist index of productivity can be written as:

$$\ln G^O = [\ln D^O(t+1) - \ln D^O(t)] - \frac{1}{2}\left[\frac{\partial \ln D^O(t+1)}{\partial t} + \frac{\partial \ln D^O(t)}{\partial t}\right] + \frac{1}{2}\sum_{k=1}^{K}[(\varepsilon(t+1)-1)e_k(t+1) + (\varepsilon(t)-1)e_k(t)]\ln\left(\frac{x_k^{t+1}}{x_k^t}\right) \quad (10)$$

where

$$\varepsilon(t) = \sum_{k=1}^{K}\frac{-\partial \ln D^O(t)}{\partial x_k} \quad \text{and} \quad e_k(t) = \frac{\partial \ln D^O(t)/\partial x_k}{\sum_{k=1}^{K}\partial \ln D^O(t)/\partial x_k} \quad (11)$$

Given the estimated parameters of the stochastic distance function (3), the calculation of the components of productivity change is rather straightforward. The change in technical efficiency (TEC) is measured by the change in the value of the output distance function from one period to the next:

$$TEC = \ln D^O(t+1) - \ln D^O(t) \quad (12)$$

Technical change (TC) includes the partial derivatives of the distance function with respect to time for the periods (t) and $(t+1)$. In an output-oriented distance function a negative (positive) sign for the parameter of the trend variable indicates technical progress (regress). In order to obtain a more intuitive result the negative sign of the second term in equation (10) transforms technical progress in a positive value and vice versa. That way we measure TC from:

$$TC = -\frac{1}{2}\left[\frac{\partial \ln D^O(t+1)}{\partial t} + \frac{\partial \ln D^O(t)}{\partial t}\right] \quad (13)$$

The the scale change effect (SC) is based on the scale elasticities $\varepsilon(t) = \sum_{k=1}^{K}\frac{-\partial \ln D^O(t)}{\partial x_k}$ and the changes in input usage[2].

$$SC = \frac{1}{2}\sum_{k=1}^{K}[(\varepsilon(t+1)-1)e_k(t+1) + (\varepsilon(t)-1)e_k(t)]\ln\left(\frac{x_k^{t+1}}{x_k^t}\right) \quad (14)$$

We observe a positive contribution to productivity change if $\varepsilon(t) > 1$ and input usage expands or if $\varepsilon(t) < 1$ and input usage is reduced. In the case of constant returns to scale ($\varepsilon(t) = 1$) or constant input quantities SC becomes zero.

[1] Regarding the theoretical foundation of the Malmquist index we refer to CAVES et al. (1982), OREA (2002), COELLI et al. (2005) and FÄRE et al. (2008).

[2] Scale elasticity is measured as the sum of the negative input distance elasticities to make the results comparable to the more common production function case.

3. Data

We employ an unbalanced panel dataset, taken from the Bavarian farm bookkeeping records (which serve as a basis for the European Commission's Farm Accountancy Data Network) with 8369 observations of 945 specialized dairy farms[3] over the years 2000 to 2008. The observations are evenly spread over the period under consideration with 8.8 observations per farm on average. 780 farms are identified as conventional farms, while 165 farms are grassland farms. Only farms operating with 100% permanent grassland during the entire observed period are considered as grassland farms. Farms with less than 95% permanent grassland are defined as conventional farms.

All monetary figures from accounting data are converted into constant price-quantity indices using price indices from the German Federal Bureau of Statistics. This deflation is done on a rather low level of aggregation (20 different price indices) in order to take account of the sometimes erratic price movements during the observation period. We aggregate outputs into two categories (*milk* and *other output*) and inputs into five categories (*labor*, *land*, *intermediate inputs*, *capital* and *herd size*). The output *milk* is measured in total revenues from milk and milk products. This allows to account for quality differences, since the price that the individual farmer receives from the processor usually varies, depending on the fat and protein content in the milk. The variable *other output* contains beef, crops and other commodities. Table 1 summarizes the descriptive statistics for the input and output variables.

Table 1: Summery statistics of input and output variables

	Mean	Max.	Min.	Std. Dev.
		Conventional		
Labor (mwu)	1.57	3.86	0.39	0.47
Land (ha)	46.5	318.3	2.7	26.5
Intermediate inputs (€)	54298	247089	3930	29501
Capital (€)	172565	940049	478	118033
Cows	36.5	134.3	4.1	15.7
Milk output (€)	75729	310611	4182	39005
Other output (€)	31958	239780	2276	18044
		Grassland		
Labor (mwu)	1.50	2.97	0.35	0.35
Land (ha)	31.2	75.1	12.3	11.8
Intermediate inputs (€)	31713	101582	5594	14851
Capital (€)	133969	495131	2600	88431
Cows	28.6	75.1	9.1	10.1
Milk output (€)	59674	181231	12741	25668
Other output (€)	17174	73825	1224	9564

Labor subsumes family and hired labor in man working units (mwu). The input variable *land* measures total cultivated land in hectare. That way, differences in land quality are omitted. We try to tackle this issue by introducing regional dummies for different agricultural production areas. The *intermediate inputs* include all expenses for forage and crop production (e.g. seed, fertilizer, pesticides, contractors), for animal production (e.g. veterinary, concentrates), for water, energy, fuel and other expenses linked to production. The variable *capital* includes the end-of-year value of buildings, technical facilities, machinery and other

[3] At least 66% of the farms total revenues have to come from milk production.

assets related to agricultural production. *Herd size* is the number of dairy cows. In addition to these main variables of the distance function, we use the farm average value of the variables "concentrate per cow" and "cattle livestock unit per ha forage area" as determinants to cluster farms with intensive and extensive production technologies.

4. Empirical Results

Utilizing Limdep 9.0 (GREENE 2007), two different LC models are estimated, one for grassland farms and one for conventional farms. Following for example OREA and KUMBHAKAR (2004), we use the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) to determine the number of classes (Table 2). For both groups the AIC and BIC indicate, that a model with two classes is preferred over one class. Attempts to estimate a model with three or more classes failed to achieve convergence in both groups.

Table 2: Information criteria for model selection

	Conventional		Grassland	
	AIC	BIC	AIC	BIC
1 class	-1.139	-1.091	-1.220	-1.073
2 classes	-1.639	-1.540	-1.741	-1.434

In estimating the LC stochastic frontier 59 % (65%) of the parameters are of statistical significance at the 5% level for the conventional (grassland) farms. Due to space limitations we omit the estimated distance function parameters and focus on the main results. The LCM identifies intensive and extensive production systems in both groups (see table 4). Moreover, both separating variables have a significant influence on the prior probabilities of class membership. The positive sign indicates, that in both groups a higher value of the variables "concentrate per cow" and "cattle livestock unit per ha forage area" increases the probability of a farm to belong to the intensive group (table 3).

Table 3: Parameter of the latent class probability function

	Conventional			Grassland		
	intensive		extensive	intensive		extensive
Constant	-3.410	(0.431)[a]	-	2.224	(1.731)	-
Concentrate/Cow	1.202	(0.231)[a]	-	0.862	(0.373)[a]	-
Cattle LU/ha forage area	1.179	(0.332)[a]	-	1.584	(0.987)[c]	-

Standard errors in parentheses
[a,b,c] Significance on the 1%,5% or 10% level

Table 4: Characteristics of identified production systems

	Conventional		Grassland	
	intensive	extensive	intensive	extensive
Observations	4078	2879	765	720
Labor (mwu)	1.62	1.50	1.55	1.45
Land (ha)	47.3	45.3	32.2	30.1
Intermediate inputs (€)	59125	47475	35313	27888
Capital (€)	182752	158163	144446	122838
Cows	38.94	33.09	29.71	27.51
Milk production (100 kg/a)	2590	1788	2009	1502
Pesticides & fertilizer/ha (€/ha)	129.1	111.5	24.9	18.6
Concentrate/Cow (€)	331.7	245.4	330.2	249.0
Cattle livestock unit/ha forage area	2.47	2.22	1.67	1.57
Milk yield (kg/cow a)	6599	5335	6694	5465
av. growth rate milk yield (%/a)	1.91	1.71	1.30	1.59
av. growth rate milk prod. (%/a)	3.15	2.16	2.67	1.69

As depicted in table 4 in both groups the intensive farms produce relatively more milk compared to an almost equal area under cultivation. The intensive farms use considerably more concentrate per cow, achieve higher milk yields per cow and have expanded their production faster than the extensive farms. The stocking rate per ha of forage area is also higher for intensive farms. Comparing the stocking rate between conventional and grassland farms, we clearly recognize the effect of higher forage yields from arable land compared to permanent grassland.

Table 5 describes the average distance elasticities and the corresponding scale elasticities for each class. In all classes the average distance elasticities show the expected sign and hence satisfy the condition of an output distance function, to be non-increasing in inputs and non-decreasing in outputs, at the mean. Output is most responsive to herd size and intermediate inputs and less responsive to land, labor and capital an all classes. The scale elasticities are calculated for each farm as the sum of the negative of the input elasticities. We find increasing returns to scale for all classes. The grassland farms exhibit higher scale elasticities and therefore seem to have a higher potential for expansion. The highest scale elasticity (1.137) is found for the class of intensive grassland farms, the lowest (1.024) for intensive conventional farms.

Table 5: Average distance elasticities for conventional and grassland dairy farms

	Conventional		Grassland	
	intensive	extensive	intensive	extensive
Labor	-0.0480	-0.0748	-0.1150	-0.0746
Land	-0.0206	-0.0443	-0.0234	-0.0286
Intermediate inputs	-0.3386	-0.3580	-0.2673	-0.3415
Capital	-0.0353	-0.0577	-0.0342	-0.0296
Herd size	-0.5818	-0.5067	-0.6971	-0.6127
Scale	1.0242	1.0415	1.1371	1.0870
Milk output	-0.8332	-0.8046	-0.9218	-0.8803
Other output	-0.1668	-0.1954	-0.0782	-0.1197

The output elasticities reflect the share of milk output in total production. As expected, milk output elasticities are higher for the grassland farms, since they more or less depend on milk production while conventional farms have more options in the mixture of their production (e.g. cultivation of cash crops).

Parameters of the stochastic frontier model are utilized to estimate the farms individual technical efficiency from $TE_i = \exp(-E(u_i|e_i))$ (see JONDROW et al. 1982). In contrast to the standard model, where we assume one homogeneous production technology, the latent class model establishes several frontiers. The farms in the sample are associated with these frontiers according to the estimated posteriori probability. The literature describes two approaches to address the issue which frontier is used as reference technology for each observation. An intuitive approach would be, to use the most likely frontier for each farm. However, this denies the uncertainty about the class membership. OREA and KUMBHAKAR (2004) describe this drawback and suggest computing efficiency scores as a weighted average for all frontiers, using the posteriori probabilities of class membership as weights.

$$TE_i = P(g|i) * TE_i|_g \qquad (15)$$

where $P(g|i)$ is the posteriori probability for a farm i to belong to class g while $TE_i|_g$ is the farms efficiency score compared to the class g frontier. Since the estimated average posteriori probabilities of class membership range between 0.987 (conventional) and 0.995 (grassland), we assume no substantial differences in the results. Thus we report efficiency scores measured against one associated frontier.

Table 6: Efficiency scores

	Conventional		Grassland	
	intensive	extensive	intensive	extensive
Mean	0.976	0.931	0.976	0.932
SD	0.007	0.043	0.008	0.044
Max	0.991	0.990	0.990	0.990
Min	0.893	0.654	0.933	0.699

We find relatively high efficiency scores ranging from 0.976 to 0.931 in all four classes. For both (conventional and grassland) groups the farms in the intensive classes are more efficient. ALVAREZ and DEL CORRAL (2010) report similar results; they ascribe these findings to the assumption, that intensive systems might be easier to manage.

The estimated parameters of the distance function are also utilized to calculate TFP change and decompose it into the components technical change (TC), technical efficiency change (TEC) and the scale change effect (SC). The grassland farms improve their productivity on average at an annual rate of 1.15% for the intensive farms and 0.93 % for extensive farms, respectively. In the conventional group the intensive (extensive) farms reach on average annual rate of 1.19% (1.0%). We depict the cumulative percentage change over time for all classes in figures 1 – 4. It becomes evident from figure 1 that both classes of grassland farms increase their productivity faster than their conventional counterparts, especially in the beginning of the observation period. However, both classes experience a decreasing productivity in the last year(s) and end up with a slightly lower cumulative percentage growth of productivity in 2008.

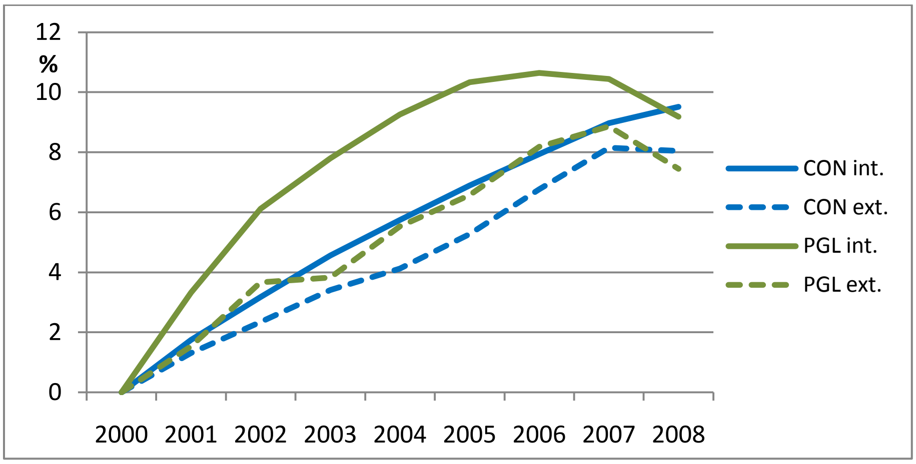

Figure 1: Cumulative percentage TFP change

In both groups (CON and PGL) intensive farms can increase their productivity to a higher level compared to the extensive farms. The TFP change for the intensive grassland farms is considerably different from the others. Growth rates are positive and relatively high in the beginning (maximum of 3.3% in 2001), but significantly negative at the end (-1.26% in 2008) of the period. All other groups seem to follow a more or less linear trend. In order to investigate the reasons for the varying TFP development we examine the behavior of the single components.

As we can see from figure 2, technical change accounts for a major part of TFP change. Hence, the development of TFP is mainly explained by the development of technical change (TC). Again we observe a strange behavior of the TC for the intensive grassland farms with technical regress in the last two years. We are unsure if this can be interpreted as a stable trend. Additional data of future years is needed for a revision.

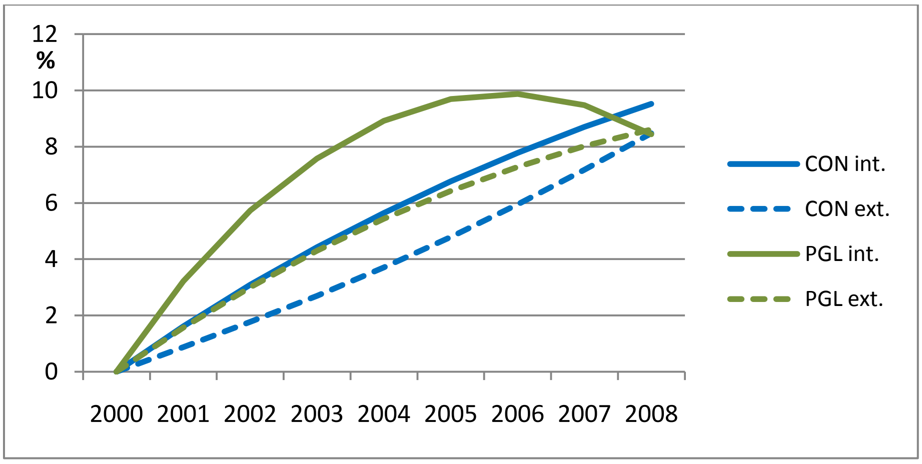

Figure 2: Cumulative percentage measure of technical change

Since technical efficiency scores are rather high for all groups, it is not surprising that the effect of TEC on productivity is relatively small. This is especially true for the intensive classes. A pattern that is common to all classes is the positive effect of improved efficiency in the years 2006 and 2007 and the rather steep drop in 2008. This can be related to the price fluctuations for milk and intermediate inputs (e.g. concentrate, fertilizer and fuel). Since we use constant price-quantity indices for the variables, prices shouldn't have any impact on the estimated distance parameters. If this is true, the interpretation of these results could be that prices have an impact on the farmer's behavior. They seem to make stronger efforts and bring their production closer to the frontier when market conditions are favorable.

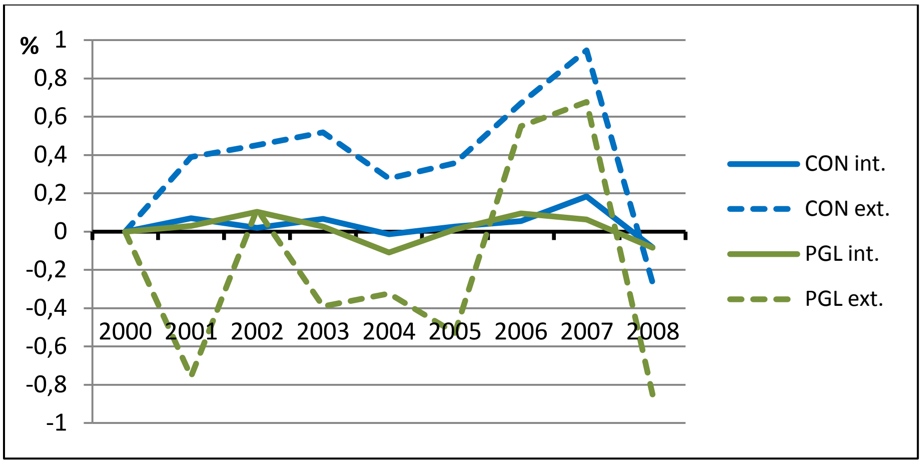

Figure 3: Cumulative percentage measure of technical efficiency change

As expected from scale elasticities in table 5, we find the greatest scale change effects for the grassland farms (figure 4). For the intensive grassland farms the expansion of input usage leads to a quite consistent positive effect on productivity. In contrast, the extensive grassland farms exhibit erratic scale change effects on productivity. The scale effect for the group of conventional farms is only small.

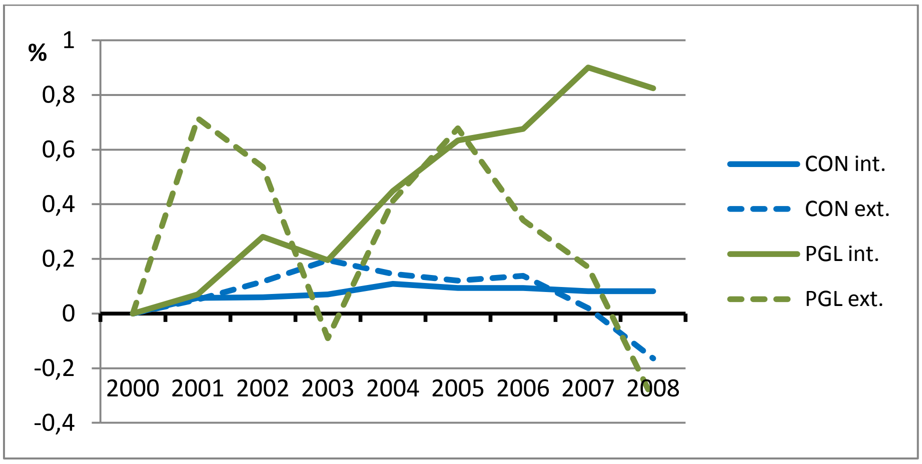

Figure 4: Cumulative percentage measure of scale change

5. Conclusions

In this paper we analyze the productivity performance of dairy farms in southern Germany. Our focus is on the comparison of farms operating on permanent grassland and conventional farms. To approach this task, we proceed in three steps. First, we split our dataset into two groups of farms, according to their share of permanent grassland. Then, for both groups a translog output distance function is estimated. We use a latent class stochastic frontier model to test the presence of heterogeneous production technologies. In the third step, we construct a generalized Malmquist productivity index to calculate and decompose TFP change for each identified group of farms.

Our analysis leads to a number of interesting results. The latent class models identify two classes in both groups differing from each other in the degree of intensification of their production technology. The farms, indentified as intensive, use more concentrate, fertilizer and pesticides, have a higher stocking rate and reach higher milk yields. These farms did also expand their milk production faster than the extensive farms. Hence, we show that the assumption of one homogenous production technology cannot be justified for both, conventional and grassland farms.

Average efficiency scores of conventional and grassland farms are not significantly different from each other. Interestingly, we find within both groups that on average intensive farms are more efficient than extensive farms. This is in line with finding by ALVAREZ and DEL CORRAL (2010) for a panel of 130 Spanish dairy farms from 1999 to 2006. Our result suggests, that the technical efficiency of the farms depends more on the intensity of the production system than on the share of permanent grassland. Considering TFP change we find that technical change is the main driving force of productivity in all classes, but with different patterns. Intensive grassland farms experience a high rate of technical progress in the first years but at a strongly decreasing rate. This leads even to technical regress in the last two years of observation. In contrast, technical progress for extensive conventional farms proceeds on a lower but increasing rate. Changes in the technical efficiency contribute to TFP change only in the extensive groups, but without a consistent negative or positive effect. All groups exhibit increasing returns to scale at the mean, but only the intensive grassland farms can benefit from a consistent positive contribution of changes in the scale of production to productivity growth. Summarizing our results, we find some evidence that permanent grassland farms can keep up with the conventional farms, in regard to productivity growth and efficiency of production. Farms with an intensive production system are more efficient and increase their productivity at a higher rate compared to extensive farms.

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