Heterogeneous Farm Output and Technical Efficiency Estimates

Heterogener Betriebsoutput und Schätzung der technischen Effizienz

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Abstract

Farmers in most OECD countries are engaged in different activities which go beyond agriculture. When assessing farm performance, it is appropriate to model these heterogeneous farm outputs separately. In this study, we use the distance function approach, which allows the consideration of technology with multiple outputs and multiple inputs. We compare estimates from single-output technology with estimates from multiple-output technology. Our empirical analysis is based on an unbalanced panel of dairy farms in the plain region of Switzerland for the period from 2003 to 2009. We choose the parametric estimation method and employ a translog specification of the production technology. The test of output separability favours a model that separately considers three different outputs: agricultural output; para-agricultural output; and direct payments. The separate modelling of direct payments has considerable influence on the estimated technology parameters as well as the technical efficiency scores. The consideration of direct payments as a separate output increases the elasticity of land by a factor greater than two and, accordingly, reduces the distance function elasticities of other inputs. The average technical efficiency estimates do not differ substantially when specifications differ. However, we reveal serious differences in the estimates of technical efficiency for individual farms. The estimated rank correlation coefficients show that the ranking of farms in terms of technical efficiency differs considerably when direct payments are modelled as a separate output.

Key Words

technical efficiency; multiple output technology; parametric output distance function; Swiss dairy farms

Zusammenfassung

Landwirtschaftliche Betriebe der meisten OECD-Länder sind in Aktivitäten involviert, welche über die reine landwirtschaftliche Produktion hinausgehen. Bei der Leistungseinschätzung der Betriebe ist es angebracht, diese heterogenen Outputs separat zu modellieren. In dieser Studie nutzen wir einen Distanzfunktion-Ansatz, welcher die Berücksichtigung von Technologie mit mehreren Outputs und mehreren Inputs ermöglicht. Wir vergleichen die Schätzungen von der Technologie mit einem Output mit den Schätzungen von der Technologie mit mehreren Outputs. Unsere empirische Analyse basiert auf einem unbalansierten Panel-Datensatz, welcher Schweizer Milchbetriebe der Talregion von 2003 bis 2009 umfasst. Wir wählen eine parametrische Schätzungsmethode und verwenden eine Translogfunktion für die Spezifizierung der Produktionstechnologie. Der Test für die Separierbarkeit der Outputs bevorzugt das Modell mit separater Betrachtung drei verschiedener Outputs: landwirtschaftlicher Output, para-landwirtschaftlicher Output und Direktzahlungen. Die separate Modellierung der Direktzahlungen hat einen erheblichen Einfluss auf die geschätzten technologischen Parameter sowie auf die technischen Effizienzwerte. Die Berücksichtigung der Direktzahlungen als separater Output erhöht die Elastizität des Inputs „Land" um mehr als das Zweifache, während die Produktivität der anderen Inputs verringert wird. Die Schätzungen der durchschnittlichen technischen Effizienz unterscheiden sich nur geringfügig zwischen den Spezifikationen. Jedoch zeigen sich beträchtliche Unterschiede in den Schätzungen der technischen Effizienz einzelner Betriebe. Die Schätzungen der Rangkorrelationskoeffizienten zeigen, dass die separate Berücksichtigung der Direktzahlungen zu grossen Unterschieden in der technischen Effizienz der Betriebe führt.

Schlüsselwörter

technische Effizienz; Technologie mit den mehreren Outputs; parametrische Output-Distanzfunktion; Schweizer Milchbetriebe

1 Introduction

Farmers produce multiple outputs which are either commodity or non-commodity goods. The latter include protection of biodiversity, maintenance of rural landscape, etc. Agricultural policies in most OECD countries recognise and promote multifunctional agriculture. For the last two decades, the support and encouragement of multifunctionality in agriculture have been important principles on the agenda of the Common Agricultural Policy (CAP). Recent reforms of the CAP (The CAP post-2013) concentrate even greater attention on non-market items produced by farms (EC, 2011a). Further, the CAP is aiming to support new economic activities for the development and competitiveness of rural areas (EC, 2011b), which implies a further diversification of farm businesses (e.g., the involvement in rural tourism, on-farm direct selling, etc.).

Since farm outputs discussed previously are heterogeneous by nature, it is appropriate to model those outputs separately when assessing farm performance. Most studies on productivity and efficiency do not consider this heterogeneity of outputs and, instead, model production technology with a single, aggregate output (FRANKSEN and LATACZ-LOHMANN, 2006; FRANKSEN et al., 2007; ABDULAI and TIETJE, 2007; TIEDEMANN and LATACZ-LOHMANN, 2011; KELLERMANN and SALHOFER, 2011). Only a few studies represent farm production technology with multiple outputs and multiple inputs (BRÜMMER et al., 2002; NEWMAN and MATTHEWS, 2007; EMVALOMATIS et al., 2011).

In this study, we evaluate farm performance by considering the heterogeneity of produced outputs, and compare the results of single and multiple output representations of production technology. In particular, we analyse Swiss dairy farms' productivity and efficiency by employing the output distance function, which allows the description of a technology with multiple outputs and multiple inputs.

Most studies on the productivity and technical efficiency of Swiss farms use data envelopment analysis (DEA), which is a deterministic approach (FERJANI, 2008; JAN et al., 2010; TODESCO et al., 2011). Only the studies of FERJANI and FLURY (2009) and BOKUSHEVA et al. (2012a) employ a stochastic representation of the production technology. Further, most of the previously listed studies use a single-output (aggregate output) representation of the production technology (except for a study by TODESCO et al., 2011). However, by employing DEA, these investigations failed to pay sufficient attention to the stochastic nature of agricultural production. Moreover, a single-output representation of the technology employed in previous studies might be especially restrictive in the context of Swiss agriculture. In particular, Swiss farmers generate a large share of their outputs with direct payments[1], which are outputs of a different nature. Furthermore, most Swiss farms are extensively involved in certain activities that go beyond agriculture, such as direct selling, agro-tourism, and many more. The general term used in Switzerland for such activities is *para-agriculture*. Para-agriculture[2] is an economic activity that is closely connected to animal husbandry, crop farming, and/or cultivation of agricultural area (SFU, 2008). Recent investigations show that approximately half of all Swiss farms carry out one or more such para-agricultural activities (FSO, 2007). As previous investigations on the performance of Swiss farms consider direct payments and para-agriculture as parts of the aggregated output, these investigations might have obtained a distorted representation of Swiss farm production technology and, thus, produced biased estimates of technical efficiency.

Therefore, this study contributes to the previous literature on productivity and technical efficiency by comparing estimates from single- (aggregate) and

[1] The current system of direct payments in Switzerland distinguishes between general and ecological direct payments. General direct payments compensate farmers for ensuring food supplies, maintaining the landscape, and contributing to preserving the social structure in rural areas. These payments are based on the area of the farms and on the amount of grazing animals. Ecological direct payments remunerate farmers for particular services, such as the creation of valuable habitats for animals and plants. These payments are paid, for example, for managing extensive meadows, and permanent flowery meadows, for organic farming, etc. (FOAG, 2004).

[2] To take into account the para-agricultural output of farms, the Swiss farm accountancy data network (FADN) distinguishes among four different farm outputs, which include agricultural output (output from agricultural activities), direct payments, output from para-agriculture, and output from non-agricultural (off-farm) activities. If para-agricultural revenue does not exceed 5,000 Swiss francs, this output is accounted for as agricultural output. On the other hand, if the revenue from para-agricultural activities is more than 250,000 Swiss francs, this output belongs to non-agricultural (off-farm) activities (SCHMID et al., 2010). Please note that in this definition of the output variables the same agricultural activity could be counted toward different output categories. However, it is not possible to get a more adequate indicator of "para-agricultural" activities in the Swiss FADN.

multiple-output representations of the production technology. We analyse Swiss farms' performance by considering the heterogeneity of their outputs and the stochastic nature of agricultural production. The stochastic distance function approach employed in this study should allow for a more adequate representation of Swiss farms' production technology and for appropriate estimates of technical efficiency. An additional study objective is to determine factors that explain the variation of technical efficiency in the farms studied.

The remaining parts of the paper are organised as follows. In the next section, we provide a short description of the distance function and its estimation techniques. Section 3 describes the data and illustrates the econometric specification of the models employed in this study. We present and discuss the results in Section 4. Finally, we summarise the main findings of this study in Section 5.

2 Methodology

2.1 Distance Function Approach

Our analysis uses the distance function approach, which provides a valuable framework for the representation of multi-input multi-output technology. Furthermore, the distance function approach allows for the specification of the technology without the need to make behavioural assumptions, such as cost-minimization or profit-maximization (COELLI et al., 2005).

Depending on the focus of the study, researchers can choose between input and output distance functions. An input distance function measures the maximum amount by which input usage can be radially reduced but still remain feasible to produce a given vector of outputs. An output distance function defines the minimum amount by which an output vector can be deflated while remaining producible with a given input vector (COELLI et al., 2005).

In this study, we use the output distance function. This function is defined on the output set, $P(\boldsymbol{x})$, as the minimum amount by which outputs can be deflated and still be technologically feasible by given inputs:

$$D_o(\boldsymbol{x},\boldsymbol{y}) = \min\{\delta : (\boldsymbol{y}/\delta) \in P(\boldsymbol{x})\}, \quad (1)$$

where $\boldsymbol{x}$ denotes the vector of inputs, and $\boldsymbol{y}$ is the vector of outputs (COELLI et al., 2005: 47).

Distance functions can be used in measuring technical efficiency. Farrell output-oriented technical efficiency *(TE)* is defined as the maximum proportional increase in outputs holding inputs fixed. The output distance function and Farrell output-oriented technical efficiency are related as follows:

$$TE = 1/D_o(\boldsymbol{x},\boldsymbol{y}). \quad (2)$$

The resulting technical efficiency scores are greater than 1. Following the empirical literature, we report the efficiency scores rescaled on the unit interval by taking the inverse of expression (2).

2.2 Estimation Methods

There are two principal methods for estimating the production and distance functions: data envelopment analysis (DEA) and stochastic frontier analysis (SFA). DEA is a non-parametric approach that uses linear programming methods for the construction of a piecewise surface (or frontier) over the data. This method does not require knowledge of the algebraic form of the production frontier (COELLI et al., 2005: 162). DEA considers the production to be deterministic and, thus, does not regard the possibility of noisy data by assumption. All deviations from the frontier are considered as inefficiency in DEA. However, it is good to mention that recent developments in DEA also allow for modeling noise in the data. The proposed approaches involve bootstrap strategies to analyse the sensitivity of efficiency scores (SIMAR and WILSON, 2000; GOCHT and BALCOMBE, 2006; HALKOS and TSEREMES, 2012) as well as constrained programming often referred to as stochastic data envelopment analysis (SDEA) (LAND et al., 1993; OLESEN and PETERSON, 1995; COOPER et al., 2002).

SFA is a parametric estimation method that assumes a given functional form for production and distance functions. The unknown parameters of the function have to be estimated by using econometric techniques (COELLI et al., 2005: 242). In the econometric estimation of distance functions, one of the outputs (in the output distance function) or inputs (in the input distance function) is factored out, and thus, the distance function is converted in an estimable regression model. The resulting model can be estimated by using conventional SFA. The general problem in estimating distance functions is that outputs (or inputs), which are used as regressors, may not be exogenous. In the context of the output distance function, BRÜMMER at al. (2002) discuss the advantages of "ratio" models (where output mixes appear as regressors) over "norm" models (where regressors are output variables scaled to unit length) and argue that the problem of endogeneity might be less severe when an output mix is used. In general, endogeneity problems appear not only in the econometric estimation of distance functions but also in production functions. Several authors discuss the endogeneity problem in the econometric estimation of production technology and use the generalised method of moments (GMM) approach to tackle this issue (ROIBAS and ARIAS, 2004; ATKISON and DORFMAN, 2005; BOKUSHEVA et al., 2012b). Other authors employ the Bayesian solution to the endogeneity problem (FERNANDEZ et al., 2000; O'DONNELL, 2011). Recently, O'DONNELL and NGUYEN (2011) suggest constructing a quantity index and factoring it out, resulting in a stochastic frontier model with uncorrelated regressors.

3 Data Description and Empirical Specification

Our investigation relies on a subsample of the Swiss FADN sample. We use unbalanced panel data for Swiss dairy farms from 2003 to 2009. Our subsample consists of conventional farms that are located in the plain region of Switzerland. In order to ensure that the analysed farms have similar production structures, we employed the following selection criteria: a) no part-time farming (off-farm income is less than 50%); b) the share of output from para-agriculture in total farm output is less than 50%; and c) the number of livestock standard-units is more than 20 but fewer than 60. As a result of this selection, the total number of observations is 927, which is 132 observations p.a., on average. The sample farms own an average of 32 livestock standard units and 24 ha of agricultural land.

The total output of farms is approximated by the so-called *'Rohertrag'*, which is the Swiss equivalent for the farm's revenue from agricultural production. This indicator of farm output consists of gross revenue from agricultural activities, gross revenue from para-agricultural activities, and direct payments. We specify three different models subject to the level of aggregation of single-output categories.

(1) First, we estimate the output distance function with one output (ODF1), where all outputs are aggregated into a single farm output (total output). This total output includes agricultural output, para-agricultural output, and direct payments.
(2) The second model is formulated as an output distance function with two outputs (ODF2): output 1 includes agricultural output and direct payments, and output 2 is defined as para-agricultural output.
(3) In the third model, we define technology as the output distance function with three outputs (ODF3): agricultural output, para-agricultural output, and direct payments.

In all three models, we use the same input variables. The vector of inputs contains: (1) land measured in hectares of farm area; (2) labour measured by man-year standard units (including both farm and hired labour); (3) livestock measured in standardised livestock units; (4) capital defined as the depreciation value of machines and buildings (in Swiss francs); (5) materials measured as costs of intermediate inputs (in Swiss francs); and (6) feed measured as costs of purchased feed (in Swiss francs). The summary statistics of the variables used are given in the appendix, Table A1.

Outputs and inputs measured in monetary units were deflated by using appropriate price indices. For agricultural output, we use the producer price index of agricultural products. Direct payments and output from para-agriculture are deflated by employing the consumer price index. To deflate capital values, we use the investment price index for agricultural goods. The purchase price indices of intermediates are used to adjust the values of the costs of the variable inputs[3].

We normalise all variables by their geometric sample mean. This procedure facilitates the convergence of the likelihood function (BRÜMMER et al., 2002) and simplifies the calculation of elasticities at the sample mean.

As mentioned previously, in the case of a parametric estimation, it is necessary to assume an appropriate functional form to represent production technology. In this study, we employ the output distance function with translog specification:

$$\ln D_{it}^{O}(\boldsymbol{y},\boldsymbol{x},t) = \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mit} + \frac{1}{2}\sum_{m=1}^{M} \sum_{n=1}^{M} \alpha_{mn} \ln y_{mit} \ln y_{nit} + \sum_{k=1}^{K} \beta_k \ln x_{kit} + \frac{1}{2}\sum_{k=1}^{K} \sum_{l=1}^{K} \beta_{kl} \ln x_{kit} \ln x_{lit} + \sum_{k=1}^{K} \sum_{m=1}^{M} \delta_{km} \ln x_{kit} \ln y_{mit} + \varepsilon_t t + \frac{1}{2} \varepsilon_{tt} t^2 + \sum_{k=1}^{K} \theta_{kt} \ln x_{kit} t + \sum_{m=1}^{M} \omega_{mt} \ln y_{mit} t \,. \quad (3)$$

[3] The price indices were provided by the Swiss Federal Office of Agriculture (FOAG, 2011), the Swiss Farmers' Union (SFU, 2011) and the Swiss Federal Statistical Office (FSO, 2011).

In equation (3), i is the farm index, k and l denote different inputs, m and n are the output indices, and t denotes time.

The output distance function is linearly homogeneous in outputs (COELLI et al., 2005: 47). We impose the homogeneity restriction by normalising the distance function in (3) by one of the outputs. This transformation enables the econometric estimation of a distance function (KUMBHAKAR and LOVELL, 2000). We normalise by output y_1. Dividing all outputs by y_1, setting $-\ln D_{it}^{O} = u_{it}$, and adding the white noise error term (v_{it}) leads to the following expression (KUMBHAKAR and LOVELL, 2000; BRÜMMER et al., 2002; NEWMAN and MATTHEWS, 2007):

$$\begin{aligned} -\ln y_{1it} = {} & \\ & \alpha_0 + \sum_{m=2}^{M} \alpha_m \ln \frac{y_{mit}}{y_{1it}} + \\ & \frac{1}{2}\sum_{m=2}^{M} \sum_{n=2}^{M} \alpha_{mn} \ln \frac{y_{mit}}{y_{1it}} \ln \frac{y_{nit}}{y_{1it}} + \sum_{k=1}^{K} \beta_k \ln x_{kit} + \\ & \frac{1}{2}\sum_{k=1}^{K} \sum_{l=1}^{K} \beta_{kl} \ln x_{kit} \ln x_{lit} + \\ & \sum_{k=1}^{K} \sum_{m=2}^{M} \delta_{km} \ln x_{kit} \ln \frac{y_{mit}}{y_{1it}} + \varepsilon_t t + \\ & \frac{1}{2} \varepsilon_{tt} t^2 + \sum_{k=1}^{K} \theta_{kt} \ln x_{kit} t + \\ & \sum_{m=2}^{M} \omega_{mt} \ln \frac{y_{mit}}{y_{1it}} t + \\ & v_{it} + u_{it} . \end{aligned} \tag{4}$$

Thus, the composite error term of the resulting model involves measurement error $v_{it} \sim N(0,\, \sigma_{v,it}^2)$ and a non-negative technical inefficiency component u_{it}. We use a half-normal model, which assumes that the inefficiency component follows a half-normal distribution, $u_{it} \sim N^{+}(0,\, \sigma_{it}^2)$. Additionally, we assume that both v and u are heteroscedastic, meaning that their variance is not constant but can be explained by several exogenous variables (KUMBHAKAR and LOVELL, 2000):

$$v_{it} \sim N(0,\, \sigma_{v,it}^2)\ with\ \sigma_{v,it}^2 = \exp(\boldsymbol{s}_{it}, \boldsymbol{\xi}) \tag{5}$$

$$u_{it} \sim N^{+}(0,\, \sigma_{u,it}^2)\ with\ \sigma_{u,it}^2 = \exp(\boldsymbol{z}_{it}, \boldsymbol{\gamma}) \tag{6}$$

where $\boldsymbol{s}$ and $\boldsymbol{z}$ are vectors of farm characteristics (q and p are indices for different farm characteristics), and $\boldsymbol{\xi}$ and $\boldsymbol{\gamma}$ are parameter vectors to be estimated.

To investigate the marginal effects of farm characteristics (exogenous variables) on farms' technical efficiency, we follow a model proposed by WANG (2002). This model assumes that the inefficiency term u_{it} follows a truncated normal distribution with mean μ_{it} and variance σ_{it}^2 ($u_{it} \sim N^{+}(\mu_{it},\, \sigma_{it}^2)$). The authors parameterise both the mean and variance of the inefficiency component as follows (WANG, 2002):

$$\mu_{it} = \boldsymbol{z}_{it} \boldsymbol{\delta}, \tag{7}$$

$$\sigma_{uit}^2 = \exp(\boldsymbol{z}_{it} \boldsymbol{\gamma}). \tag{8}$$

In this model, $\boldsymbol{z}_{it}$ denotes the vector of variables (several farm characteristics) which are associated with the inefficiency of farms, and $\boldsymbol{\delta}$ and $\boldsymbol{\gamma}$ are the corresponding parameter vectors to be estimated. Since we use a half-normal model, our model is a special case of the model proposed by WANG (2002) and is obtained by substituting zero for $\boldsymbol{\delta}$ in (7).

The marginal effect of z variables on the expected value of inefficiency $E(u_{it})$ is (Wang, 2002):

$$\frac{\partial E(u_{it})}{\partial z_p} = \gamma_p \frac{\sigma_{it}^2}{2} \left[\frac{\phi(\Lambda)}{\Phi(\Lambda)} \right]. \tag{9}$$

The marginal effect of z variables on inefficiency variance $V(u_{it})$ is (WANG, 2002):

$$\frac{\partial V(u_{it})}{\partial z_p} = \gamma_p \sigma_{it}^2 \left\{ 1 - \left[\frac{\phi(\Lambda)}{\Phi(\Lambda)} \right]^2 \right\}. \tag{10}$$

In expressions (9) and (10), E denotes the expected value, V is the variance, γ_p is the parameter associated with z, $\Lambda = \mu_{it}/\sigma_{uit}$ (in our case, Λ is equal to zero), and ϕ and Φ are the probability and cumulative density functions of the standard normal distribution, respectively.

Following the empirical literature, we employ several farm characteristics to explain heteroscedastic u_{it} and to test hypotheses regarding the influence of these characteristics on farm technical efficiency:

- (z1) farmers' age. We expect that age has a negative effect on technical efficiency. Recent studies on Swiss farms (FERJANI, 2008; JAN et al., 2010) find a negative influence of this variable. The empirical literature reports dissimilar results regarding the impact of age on the technical efficiency of farms. The negative impact (BRÜMMER and LOY, 2000; KARAGIANIAS et al., 2006; THIRTLE and HOLDING, 2003; HADLEY, 2006) is often explained by the fact that older farmers tend to have less motivation to adopt new technologies. The positive impact of this variable (WILSON et al., 2001; O'NEILL and MATTHEWS, 2001; MATHIJS and VRANKEN, 2001; BARNES, 2006) is associated with being more experienced.
- (z2) farmers' education. We hypothesise that education positively influences farm technical

efficiency. Farmers with a higher educational level are often found to perform better, since they might make better use of inputs, adopt new technology faster, etc. (LIU and ZHUANG, 2000; WILSON et al., 2001; O'NEIL and MATTHEWS, 2001; MATHIJS and VRANKEN, 2001; IGLIORI, 2005). However, other studies (JAN et al., 2010; GOODWIN and MISHRA, 2004; BARNES, 2006; LAKNER, 2009) do not observe any significant impact of this variable on technical efficiency.

- (z3) share of rented land. We hypothesise a negative impact of this variable on technical efficiency. The empirical literature shows that farmers tend to manage their own land more efficiently (MATHIJS and VRANKEN, 2000; THIRTLE and HOLDING, 2003; HADLEY, 2006).
- (z4) share of hired labour. We expect a negative influence of this variable on technical efficiency. In line with the principal agent theory, farms with a higher level of hired employees are expected to have higher transaction costs (e.g., for controlling). Consequently, this might lead to a lower technical efficiency of these farms. Results confirming this hypothesis are reported by MATHIJS and VRANKEN (2000), KARAGIANNIS et al. (2006), and CABRERA et al. (2010).
- (z5) share of off-farm income in total farm income. We expect a negative effect of off-farm employment on technical efficiency, because it might distract the farmer's attention from his main activity - agricultural production. Farmers with more off-farm work could have lower motivation and less time available for farming. This hypothesis (negative influence) is confirmed in several studies (O'NEILL and MATTHEWS, 2001; BRÜMMER et al., 2001; GOODWIN and MISHRA, 2004; JAN et al., 2010). Other studies (HUFFMAN and EVENSON, 2001; MATHIJS and VRANKEN, 2001; TONSOR and FEATHERSTONE, 2009), however, report positive influence of this variable on technical efficiency.
- (z6) share of para-agriculture in total farm output. We expect a positive effect of para-agriculture on technical efficiency. These activities might require lower input use per unit of output, and, thus, farms with higher share of para-agriculture could be more efficient. JAN et al. (2010) find positive impact of increasing para-agricultural activities on the technical efficiencies of dairy farms located in the mountainous region of Switzerland.
- (z7) ecological direct payments. We hypothesise a negative effect of ecological direct payments on technical efficiency. Farms receiving higher payments are strongly dependent on the support from policy instruments. This might lead to lower technical efficiency of such farms. The empirical literature reports contradictory results regarding the influence of direct payments on farms' technical efficiency. While FERJANI (2008) shows a negative relationship between direct payments and the technical efficiency of Swiss farms, the study by JAN et al. (2010) find this relationship to be positive. LAKNER (2009) observes lower efficiency scores for German milk farms, which receive higher agri-environmental payments.
- (z8) altitude of the farmland. We suppose that increasing altitude aggravates production conditions and, hence, negatively influences technical efficiency. For example, the study by BRÜMMER and LOY (2000) supports this hypothesis. The study of JAN et al. (2010) also observes a negative impact of altitude on the technical efficiency of Swiss farms in the mountainous region. It is obvious that the influence of altitude is more pronounced there than in the plain region of Switzerland. However, we still test the influence of this variable in our analysis, because the altitudes of the farms in our sample (farms in the plain region) vary from 350 to 1,050 metres above sea level.

Additionally, we use logged inputs (z9-z14) as well as log output ratios (z15-z16) as explanatory variables of heteroscedastic u_{it}.

For the heteroscedasticity in the noise component, v_{it}, we include eight variables (s1-s8): age, education, rented land, share of hired labour, share of off-farm income, share of para-agriculture, ecological direct payments, and altitude.

4 Results and Discussion

4.1 Testing

As mentioned in the previous section, we estimate three different models (ODF1, ODF2, and ODF3). In order to identify whether it is appropriate to have one, two, or three outputs, we conduct separability tests. If the production technology is separable in outputs, then it is appropriate to aggregate different outputs into a single output. Several authors discuss the test for the separability of the translog functional form. Earlier

Table 1. Results of the likelihood ratio test* for separability

	Log likelihood	Likelihood ratio (λ)	Critical value (1%)	Outcome
Hypotheses for ODF 2				
H_A: Full model (with all cross terms)	710.37			
H_{01}: Coefficients of all cross terms between y2 and inputs equal to zero	693.62	33.50	16.81	Reject H_0
Hypotheses for ODF 3				
H_A: Full model (with all cross terms)	936.97			
H_{01}: Coefficients of all cross terms between y2 and inputs equal to zero	915.33	43.28	16.81	Reject H_0
H_{02}: Coefficients of all cross terms between y3 and inputs equal to zero	897.17	79.60	16.81	Reject H_0
H_{03}: H_{01} and H_{02}	876.58	120.78	26.22	Reject H_0

*The likelihood ratio statistic is computed as follows: $\lambda = -2\ [LL\ (H_0) - LL\ (H_A)]$, where $LL(H_0)$ is the value of the log-likelihood function under a null hypothesis (restricted model), and $LL(H_A)$ denotes the log-likelihood function under an alternative hypothesis (unrestricted model).
Source: Authors' calculations

empirical literature uses the Berndt-Christensen (BERNDT and CHRISTENSEN, 1974) framework to test for separability. However, the Berndt-Christensen test is a joint test of weak separability and the linear logarithmic aggregator function (BLACKORBY et al., 1977; WOODLAND, 1978). The imposition of the parametric restrictions to the translog function adds further structure to the function by requiring the aggregator function to be linear logarithmic (WOODLAND, 1978). As a solution, WOODLAND (1978) suggests working with a variable profit function rather than a production function, and formulating the test for separability by requiring all cross-terms between inputs and outputs to be equal to zero. In this way, the existence of an aggregator may be tested without further unwanted structure being imposed (WOODLAND, 1978: 385). The same test is applicable in testing separability in the output distance function (IRZ and THIRTLE, 2004; NEWMAN and MATTHEWS, 2007). Thus, we test the hypothesis of separability by imposing the following restriction on expression (4): $\delta_{km} = 0$. Table 1 presents the results of testing the ODF2 and ODF3 models.

In all cases, separability (i.e., null-hypothesis that cross-terms between inputs and outputs equals zero) is strongly (at 1% significance level) rejected, confirming that it is not appropriate to aggregate different outputs into a single output. Thus, the outcome of these tests justifies the use of the distance function rather than the production function for the technology representation of the sample farms. Moreover, according to our results, it is better to consider the three different outputs separately. Therefore, we choose the ODF3 model, and most parts of the following results and discussions apply to preferred model.

Next, we test for heteroscedasticity in the error terms. Table 2 presents the results of three likelihood ratio tests for heteroscedasticity: (i) in both u and v; (ii) only in v; and (iii) only in u.

Table 2. Results* of the likelihood ratio test for heteroscedasticity in *v* and *u*

Hypotheses	Log likelihood	Likelihood ratio (λ)	Critical value (1%)	Outcome
H_A: Double heteroscedasticity (in v, in u)	936.97			
H_{0i}: Homoscedasticity in both v and u	831.41	211.12	42.98	Reject H_0
H_{0ii}: Homoscedasticity in v (and heteroscedasticity in u)	916.76	40.42	20.09	Reject H_0
H_{0iii}: Homoscedasticity in u (and heteroscedasticity in v)	835.59	202.76	32.00	Reject H_0

* Presented results are for the ODF 3model. We conducted the same tests for the ODF2 and ODF1 models, and double heteroscedasticity was preferred in those models, too.
Source: Authors' calculations

Table 3. Elasticities of distance function and returns to scale

	Elasticities at sample mean	Significance[1]	Standard error
Agricultural output**	0.524		
Para-agricultural output	0.006	***	0.002
Direct payments	0.470	***	0.026
Land	0.390	***	0.041
Labour	0.124	***	0.035
Capital	0.097	***	0.020
Livestock	0.361	***	0.046
Intermediates	0.079	***	0.025
Feed	0.048	***	0.015
Returns to scale	1.100	**	0.181

[1] *** significant at 1% , ** significant at 5%, * significant at 10% , n. s. not significant.
[2] The distance elasticity of agricultural output, y_l is: $\varepsilon_{y_1} = 1 - \sum_{m=2}^{M} \varepsilon_{y_m}$.
This follows from the homogeneity restriction: $\sum_m \alpha_m = 1, m = 1, 2, \ldots, M$.
Source: Authors' calculations

All three null hypotheses (homoscedasticity in both v and u; homoscedasticity in v; and homoscedasticity in u) are rejected at 1% significant level. These results imply the presence of technical inefficiency effects in this study and, in addition to that, justify using the double heteroscedasticity model.

4.2 Parameter Estimates

In this chapter, we report the results of an estimated distance function with three different outputs (the ODF3 model)[4]. As we normalise all variables by their sample means, the first-order estimates in our translog models can be interpreted as elasticities at the sample mean. Table 3 summarises the distance elasticities, the elasticities for inputs, and the returns to scale.

In the distance function models, the coefficient estimates with respect to the output show the relative contribution of single outputs to the distance function value. According to the estimates, an increase of the agricultural output by 1% increase the value of the distance function by 0.524% *ceteris paribus*. Para-agriculture and direct payments increase the distance function by 0.006% and 0.470%, respectively. Furthermore, under revenue maximization, the output distance elasticities should be equal to the revenue shares of the corresponding outputs (BRÜMMER et al., 2002). The estimated elasticities for agricultural output (0.524) as well as for para-agriculture (0.006) are a bit low, as the average shares of agricultural output and para-agriculture are 78% and 3.3%, respectively. On the other hand, the estimated elasticity of direct payments (0.470) is much higher than the share of this output (18.2%). This might be connected to the fact that the "production" of some part of direct payments (especially general direct payments) does not require any inputs or trade-offs with other outputs. Thus, these results suggest a strong influence of direct payments on farm production decisions.

All first-order terms of input variables (land, labour, capital, animals, intermediates, and feed) are significant at the 1% level. We found relatively high elasticities for land and livestock, suggesting that these two inputs contribute the most to production. Table 3 shows that the production technology exhibits returns to scale over one. The null hypothesis of constant returns to scale is rejected at a 5% level, suggesting a variable return to scale at the sample mean.

Further, the elasticities of single inputs differ significantly in the three considered specifications (cf. estimates in Table A2). In the first and second specifications, the elasticities of inputs are very similar, whereas the model with three different outputs shows another picture. The ODF3 model reveals the estimated elasticity of land to be higher than that in the other two models. This rise in elasticity with respect to land in the ODF3 model leads to the particularly lower elasticities of other inputs. This result, again, suggests that the producers' resource allocation and factor remuneration might be completely different when direct payments are considered as a separate output.

[4] We give parameter estimates from all three models in the appendix, Table A2.

We check the theoretical consistency of the employed distance function. For most functional forms applied in economic analysis, there is a trade-off between flexibility and theoretical consistency (SAUER et al., 2006). Since the translog function (which is a flexible functional form) fails to satisfy monotonicity and curvature globally, it is appropriate to check these conditions locally (MOREY, 1986; SAUER et al., 2006).

The monotonicity is fulfilled at the sample mean: the estimated distance function is non-increasing in all inputs (as indicated by the elasticities of distance function with respect to *k* inputs) and non-decreasing in all outputs (as indicated by the elasticities with respect to *m* outputs). Additionally, we test whether the output distance function was convex in outputs. For this we evaluate Hessian matrix of outputs: $H_{output} = \begin{bmatrix} -0.005 & 0.005 \\ 0.005 & -0.665 \end{bmatrix}$. Since both Eigenvalues are negative, we conclude that convexity is not satisfied for the estimated distance function (Hessian matrix was expected to be semi-positive). This implies that the reported results on the estimated parameters should be taken with caution. Furthermore, the theoretical inconsistency has also consequences with regard to the estimated technical efficiency. The violation of convexity means that the estimated function does not represent the maximal possible output combination at each point. Therefore, this would possible lead to an overestimation of technical efficiency scores of some farms.

4.3 Technical Efficiency

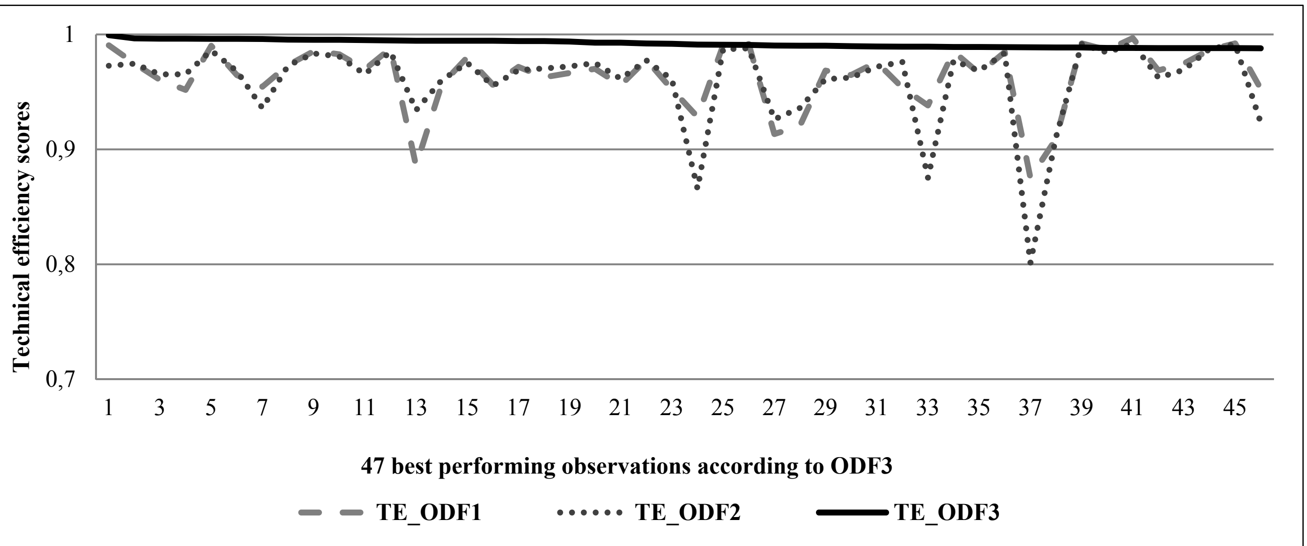
The results of this study reveal the mean technical efficiency for sample farms to be 0.95 (estimated with the ODF3 model). The efficiency scores range from 0.71 to 1.00 (standard deviation = 0.04).

The mean technical efficiency obtained in this study is higher than that estimated in other studies for Switzerland. JAN et al. (2010) calculates the technical efficiency of Swiss dairy farms located in the mountainous region to be about 75%, on average. FERJANI (2009) reports the mean efficiencies of farms in plain, hill, and mountain regions of Switzerland to be 77%, 68%, and 57%, respectively. Both studies, however, use data envelopment analysis (DEA). Accordingly, both previously mentioned studies might have underestimated the technical efficiency of Swiss farms, since by accounting for all deviations from the best practices as inefficiencies, DEA provides lower scores for technical efficiency. Another explanation for the high values of technical efficiency could be that the farms investigated in our study are conventional, 'big', and full-time farms (as a consequence of our selection criteria), and do not reflect the overall heterogeneity of the Swiss dairy sector. The studies mentioned previously distinguish neither between organic and conventional farms, nor between part- time and full-time farms.

We observe the mean efficiency scores to be 0.93, 0.93, and 0.95 for ODF1, ODF2, and ODF3, respectively. The efficiency scores of farms ranged from 0.61 to 1.00 (S.D. = 0.06) in the case of ODF1, from 0.65 to 1.00 (S.D. = 0.06) in ODF2, and from 0.71 to 1.00 (S.D. = 0.04) in ODF3.

The individual technical efficiency scores differ in the three model specifications. Figure 1 presents the comparison of the individual technical efficiency estimates for the best-performing farms.

Figure 1. Estimates of technical efficiency with three different models (ODF1, ODF2, ODF3)



Source: Authors' representation

The solid line in Figure 1 presents the technical efficiency scores for the 47 (5%) best-performing observations obtained from the ODF3 model (preferred model). The dashed lines in this figure show the technical efficiency estimates for the same farms, according to the ODF2 and ODF1 models. A comparison of these estimates reveals a clear underestimation of the technical efficiency for the considered farms when employing ODF2 or ODF1 models. Figure 1 also shows that the composition of the frontier very much depends on the model specification.

However, since the mean efficiencies obtained from different models are quite similar (0.93, 0.93, and 0.95 in ODF1, ODF2, and ODF3, respectively), the underestimation of efficiency scores for the best performing farms must be accompanied by an overestimation of the technical efficiency of some other farms. When investigating differences for the whole sample, we observe that overestimation mainly occurs for the worst-performing farms (see Figure A1 and Figure A2 in the Appendix).

These results could be explained by the fact that in the ODF3 approach, we consider direct payments separately. Obviously, the ODF2 and ODF1 specifications (when direct payments are aggregated with other outputs) do not allow for adequate consideration of this farm output.

For further investigation of the technical efficiency scores, we estimate the rank correlations among the scores resulted in three different models. The results of these estimations are given in Table 4.

As indicated in Table 4, the correlation between the efficiency estimates in the ODF2 and ODF1 models is relatively high. On the contrary, the rank correlation is considerably low between the estimates in ODF3 and ODF2 as well as between the estimates in ODF3 and ODF1. Again, this confirms that the separate consideration of direct payments in the specification of production technology has a major impact on the results.

Table 4. Correlations between technical efficiency scores estimated with three different models

	ODF1 - ODF2	ODF1 - ODF3	ODF2 - ODF3
Spearman’s rank correlation coefficient	0.842***	0.226***	0.351***
Kendall’s rank correlation coefficient	0.698***	0.153***	0.242***

Source: Authors’ calculations

4.4 Effect of Farm Characteristics

The following farm characteristics show significant influence on the technical efficiency of the sample farms: share of rented land (positive); share of hired labour (positive); share of off-farm income (negative); share of para-agriculture (negative); and ecological direct payments per animal (positive). We do not find significant effects of the variables age, education, and altitude. As already mentioned, we also included the logged inputs as well as the log output ratios for heteroscedasticity in u_{it}. Most of these variables (logged inputs and the log output ratios) are excluded as a result of the likelihood ratio tests. Only logged land and logged labour are significant (see Table A2 in the Appendix).

As mentioned, we also calculate the marginal effect of farm characteristics on the expected value and variance of the inefficiency component (expressions (8) and (9)). Table 5 presents the average marginal effects that resulted in the ODF3 model.

The variables age (z1), education (z2), and altitude (z8) are not significant in this study. As discussed in Chapter 3, empirical results of sociological variables (age and education) are dissimilar. The result regarding altitude might be connected to the fact that our sample includes only farms in the plain region of Switzerland, and altitude seems to be a less influential factor there.

The results of this study confirm our hypothesis (see Chapter 3) regarding the negative influence of the share of off-farm income (z5). For other variables, the findings of this study are contrary to our hypothesis. The positive effect of the share of rented land (z3) might be explained by the fact that farms with a higher share of rented land tend to be larger and, therefore, they might have higher efficiency scores. The same reason might cause the positive influence of the share of hired labour (z4), since larger farms tend to hire a

Table 5. The average marginal effect of farm characteristics on E(u_{it}) and V(u_{it})

Variable	on E(u_{it})	on V(u_{it})
Share of rented land	-.00035	-.00003
Share of hired labour	-.00070	-.00007
Share of off-farm income of total farm income	.00102	.00010
Share of para-agriculture in the total farm output	.00120	.00012
Ecological direct payments per animal	-.00030	-.00003

Source: Authors’ calculations

more labour. The reason for the negative influence of share of para-agriculture (z6) might be associated with the fact that para-agricultural activities (similar to off-farm activities) could distract farmers from their main activities. The positive influence of ecological direct payments (z7) might be connected to the fact that environmental protection does not necessarily increase production costs.

In general, we observe very small marginal effects of farm characteristics on the expected value of u_{it} as well as on the variance of u_{it} (see Table 5). This indicates the rather negligible impact (in economic terms) of these variables on the technical efficiency of sample farms.

5 Conclusions

The main purpose of this study is to analyse the production technology and technical efficiency of farms by considering different farm outputs. We estimate the technical efficiency of farms by using the multiple-output, multiple-input representation of the production technology, and compare the results with the single output representation of the technology. The analysis uses unbalanced panel data for Swiss dairy farms for the period of 2003 to 2009.

This study shows that the separate consideration of direct payments causes a substantial increase in the elasticity of land and, respectively, lower elasticities of the remaining production factors. This finding suggests that the remuneration of Swiss farms for the provision of positive externalities (or for the reduction of negative externalities) seriously influences the resource-allocation decisions of farmers. As most of these payments are bound to land input, we observe a high elasticity for this input.

The choice of specification (single-output vs. multi-output technology) does not produce much difference in terms of the average estimates of technical efficiency. However, depending on the specification, individual efficiency scores differ considerably in the specifications. The estimated rank correlation coefficients show that the model with three outputs ranks farms differently with respect to technical efficiency.

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Appendix

Table A1. Descriptive statistics of the variables used (927 observations)

	Mean	Std. dev.	Min	Max
Outputs				
Agricultural output in Swiss francs	205601.80	71624.97	83454.10	614488.10
Para-agricultural output in Swiss francs	8983.37	19606.09	0.00	231308.80
Direct payments (general and ecological) in Swiss francs	46069.90	16063.49	18275.50	148806.00
Share of agricultural output in total farm output (in %)	78.54	7.68	49.80	92.61
Share of para-agriculture in total farm output (in %)	3.26	6.28	0.00	39.94
Share of direct payments in total farm output (in %)	18.20	5.20	6.73	35.41
Inputs				
Land in ha	23.92	7.14	10.84	60.07
Labor in man-year standard units	1.70	0.48	0.89	3.92
Capital in Swiss francs	38222.86	16390.67	4528.00	118611.40
Livestock in standardized livestock units	32.43	8.85	20.09	59.88
Intermediates in Swiss francs	78466.61	35508.08	21258.02	384117.00
Feed in Swiss francs	24610.55	20586.55	1859.83	207530.70
Farm characteristics				
Age	45.00	8.99	23.00	65.00
Education	3.37	0.69	1.00	5.00
Share of rented land (in %)	43.66	28.82	0.00	100.00
Share of hired labor (in %)	18.07	18.21	0.00	71.68
Share of off-farm income (in %)	14.63	12.20	0.00	49.59
Share of para-agriculture (in %)	3.26	6.28	0.00	39.94
Ecological direct payments per animal (in Swiss francs)	303.27	110.00	0.00	1093.46
Altitude (in metres above sea level)	540.66	93.33	350.00	1050.00

Source: Authors' calculations

Table A2. Parameter estimates of distance functions

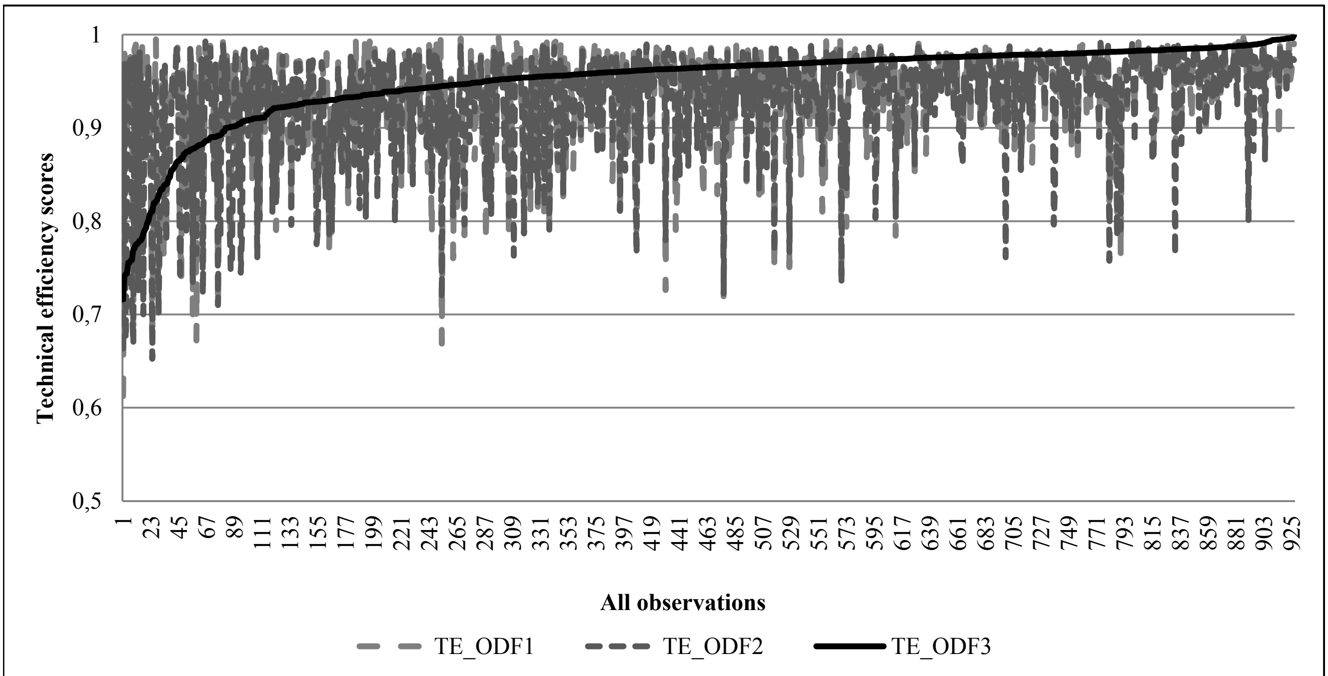
		ODF 3			ODF 2			ODF1		
Variables	**Coef.**	**Estimat.**	**S.E.**	**P-value**	**Estimat.**	**S.E.**	**P-value**	**Estimat.**	**S.E.**	**P-value**
constant	α_0	-0.035	0.018	0.057	-0.069	0.022	0.001	-0.019	0.019	0.312
y2 *para*	α_2	0.006	0.002	0.001	0.011	0.002	0.000	---	---	---
y3 *d. p.*	α_3	0.470	0.026	0.000	---	---	---	---	---	---
y2y2	α_{22}	0.001	0.000	0.002	0.001	0.000	0.000	---	---	---
y3y3	α_{33}	-0.416	0.056	0.000	---	---	---	---	---	---
y2y3	α_{23}	0.002	0.002	0.484	---	---	---	---	---	---
xl *land*	β_1	-0.390	0.041	0.000	-0.139	0.040	0.001	-0.138	0.040	0.001
xw *labor*	β_2	-0.124	0.035	0.000	-0.116	0.037	0.002	-0.099	0.037	0.007
xk *capit.*	β_3	-0.097	0.020	0.000	-0.158	0.022	0.000	-0.157	0.021	0.000
xa *livest.*	β_4	-0.361	0.046	0.000	-0.498	0.055	0.000	-0.437	0.058	0.000
xm *mater.*	β_5	-0.079	0.025	0.001	-0.105	0.033	0.001	-0.158	0.033	0.000
xf *feed*	β_6	-0.048	0.015	0.002	-0.072	0.017	0.000	-0.052	0.017	0.003
xll	β_{11}	-0.087	0.113	0.440	-0.072	0.114	0.530	-0.062	0.108	0.564
xww	β_{22}	0.059	0.088	0.503	0.146	0.103	0.157	0.019	0.102	0.854
xkk	β_{33}	-0.055	0.029	0.056	-0.095	0.029	0.001	-0.100	0.029	0.000
xaa	β_{44}	0.172	0.195	0.377	0.540	0.233	0.020	0.421	0.231	0.068
xmm	β_{55}	-0.129	0.055	0.019	-0.080	0.064	0.212	-0.172	0.067	0.010
xff	β_{66}	-0.067	0.016	0.000	-0.047	0.021	0.025	-0.059	0.021	0.005
xlw	β_{12}	0.082	0.137	0.549	-0.130	0.152	0.395	-0.049	0.148	0.740
xlk	β_{13}	0.061	0.112	0.584	0.004	0.095	0.962	0.026	0.093	0.783
xla	β_{14}	-0.396	0.223	0.076	-0.609	0.257	0.018	-0.679	0.254	0.008
xlm	β_{15}	-0.036	0.126	0.776	0.018	0.141	0.900	0.163	0.138	0.239
xlf	β_{16}	0.267	0.063	0.000	0.296	0.084	0.000	0.208	0.083	0.012
xwk	β_{23}	-0.008	0.080	0.924	0.010	0.083	0.900	-0.074	0.085	0.383
xwa	β_{24}	-0.344	0.174	0.049	-0.188	0.219	0.391	-0.069	0.214	0.746
xwm	β_{25}	0.126	0.104	0.225	0.039	0.122	0.751	-0.223	0.117	0.057
xwf	β_{26}	0.001	0.055	0.982	-0.004	0.068	0.955	0.029	0.066	0.661
xka	β_{34}	0.236	0.110	0.031	0.267	0.114	0.020	0.301	0.115	0.009
xkm	β_{35}	-0.011	0.059	0.850	0.029	0.065	0.659	-0.008	0.066	0.901
xkf	β_{36}	-0.057	0.038	0.135	-0.024	0.040	0.545	-0.027	0.040	0.493
xam	β_{45}	0.114	0.147	0.441	-0.270	0.180	0.134	-0.057	0.182	0.752
xaf	β_{46}	-0.145	0.091	0.110	-0.350	0.113	0.002	-0.330	0.117	0.005
xfm	β_{56}	0.090	0.048	0.058	0.144	0.060	0.018	0.188	0.061	0.002
xly2	δ_{12}	0.001	0.002	0.620	0.002	0.002	0.363	---	---	---
xwy2	δ_{22}	-0.008	0.002	0.000	-0.008	0.002	0.000	---	---	---
xky2	δ_{32}	0.000	0.001	0.958	-0.002	0.001	0.084	---	---	---
xay2	δ_{42}	-0.006	0.002	0.005	-0.006	0.003	0.024	---	---	---
xmy2	δ_{52}	0.002	0.001	0.090	0.003	0.002	0.107	---	---	---
xfy2	δ_{62}	0.000	0.001	0.682	0.000	0.001	0.669	---	---	---
xly3	δ_{13}	0.185	0.052	0.000	---	---	---	---	---	---
xwy3	δ_{23}	0.008	0.047	0.859	---	---	---	---	---	---
xky3	δ_{33}	0.002	0.036	0.963	---	---	---	---	---	---
xay3	δ_{43}	0.070	0.068	0.298	---	---	---	---	---	---
xmy3	δ_{53}	-0.092	0.043	0.033	---	---	---	---	---	---
xfy3	δ_{63}	-0.122	0.022	0.000	---	---	---	---	---	---
t *time*	ε_t	0.022	0.007	0.002	0.004	0.009	0.664	0.010	0.009	0.247
tt	ε_{tt}	-0.010	0.002	0.000	-0.004	0.002	0.066	-0.005	0.002	0.020
xlt	θ_{1t}	0.006	0.009	0.476	0.012	0.010	0.235	0.015	0.010	0.129
xwt	θ_{2t}	0.014	0.007	0.043	0.025	0.008	0.003	0.018	0.008	0.036
xkt	θ_{3t}	0.000	0.004	0.997	-0.004	0.005	0.384	-0.007	0.005	0.119
xat	θ_{4t}	-0.001	0.011	0.915	0.023	0.013	0.082	0.026	0.013	0.053
xmt	θ_{5t}	-0.005	0.006	0.401	-0.013	0.007	0.069	-0.015	0.007	0.040
xft	θ_{6t}	0.004	0.003	0.233	0.005	0.004	0.228	0.002	0.004	0.593
y2t	ω_{2t}	0.000	0.000	0.780	-0.001	0.000	0.008	---	---	---
y3t	ω_{3t}	0.017	0.006	0.004	---	---	---	---	---	---

Table A2 (continued)

Usigmas										
constant	γ_0	-8.519	2.178	0.000	-69.612	8.286	0.000	-84.998	9.246	0.000
z1*	γ_1	---	---	---	---	---	---	---	---	---
z2	γ_2	---	---	---	---	---	---	---	---	---
z3	γ_3	-0.014	0.006	0.012	---	---	---	---	---	---
z4	γ_4	-0.028	0.008	0.001	-0.026	0.007	0.000	-0.024	0.007	0.001
z5	γ_5	0.041	0.009	0.000	0.033	0.008	0.000	0.034	0.008	0.000
z6	γ_6	0.048	0.018	0.010				-0.165	0.031	0.000
z7	γ_7	-0.012	0.001	0.000	-0.007	0.001	0.000	-0.008	0.001	0.000
z8	γ_8	---	---	---	---	---	---	---	---	---
z9	γ_9	---	---	---	---	---	---	---	---	---
z10	γ_{10}	---	---	---	58.321	5.558	0.000	63.097	6.056	0.000
lnl	γ_{11}	1.773	0.719	0.014	-2.853	0.836	0.001	-3.441	0.892	0.000
lnw	γ_{12}	1.780	0.841	0.034	---	---	---	---	---	---
lnk	γ_{13}	---	---	---	1.197	0.413	0.004	1.858	0.419	0.000
lna	γ_{14}	---	---	---	---	---	---	-2.027	0.941	0.031
lnm	γ_{15}	---	---	---	1.057	0.431	0.014	2.270	0.525	0.000
lnf	γ_{16}	---	---	---	---	---	---	---	---	---
vsigmas										
constant	ξ_0	-4.678	0.631	0.000	-1.836	0.481	0.000	-2.249	0.421	0.000
s1	ξ_1	-0.026	0.007	0.000	---	---	---	---	---	---
s2	ξ_2	-0.173	0.104	0.098	---	---	---	---	---	---
s3	ξ_3	---	---	---	-0.013	0.003	0.000	-0.012	0.002	0.000
s4	ξ_4	---	---	---	---	---	---	---	---	---
s5	ξ_5	-0.016	0.006	0.012	-0.034	0.007	0.000	-0.041	0.007	0.000
s6	ξ_6	---	---	---	---	---	---	---	---	---
s7	ξ_7	0.003	0.001	0.000	---	---	---	---	---	---
s8	ξ_8	0.001	0.001	0.048	-0.003	0.001	0.000	-0.002	0.001	0.001

* First, we included all z and s variables described in Chapter 3. For each model (ODF1, ODF2, and ODF3), we conducted backward selection of these variables, in order to test whether they can be excluded or not. Table A2 presents parameter estimates for three final models.
Source: Authors' calculations

Figure A1. Technical efficiency scores of all observations estimated with three different models (ordered according to ODF3)



Source: Authors' representation