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Why considering technological heterogeneity is important for evaluating farm performance?

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Abstract

A split-panel latent class stochastic frontier model is applied to account for technological heterogeneity among Swiss dairy farms and to assess the potential performance improvements through technology choice and change over 11 years. Three technology classes with substantially different productivity levels are identified considering the unobserved and observed farm characteristics. Technologies seem on average well adapted to local natural production conditions with low potential for efficiency and productivity increases. Few farms changed technology over time and either an intensification or extensification strategy was observed. Policymakers must be aware of the interlinkages between technology choices and the economic situation of farms.

Keywords: productivity, efficiency, latent class model, stochastic frontier, dairy farm

JEL classification: Q12, D24

1. Introduction

Agricultural policies in Europe aim to ensure appropriate income levels and long-term economic viability of farms (European Court, 2016). In the Swiss Federal Constitution, Article 104 states that the government supplements farmers' incomes with direct payments to achieve an appropriate remuneration for the services provided, subject to proof of ecological performance. Article 5 of the Federal Act on Agriculture specifies 'The measures in this Act aim to ensure that farms run on a sustainable basis and which are economically efficient can achieve incomes over a period of several years that are comparable to incomes in other sectors in the same region'. Based on this policy background, productivity and efficiency analysis is used to evaluate the performance of farms and provide recommendations to policymakers, farm advisors and farmers on how to reduce inefficiencies. Empirically, inefficiencies are

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represented by deviations of individual farm input and output observations from the production possibility frontier of the best-practice farms.

One of the main challenges in empirical applications is to identify the inefficiencies resulting from non-optimal management and separate out deviations due to differences in the production technology, i.e. heterogeneity between production technology groups of farms. With respect to the interrelations between agricultural policies and farmers' input allocation decisions, existing research shows diverse effects of public subsidies on farm technical efficiency (Minviel and Latruffe, 2017). For instance, farmers value animal welfare besides mere profits, which may result in seemingly inefficient resource use allocation decisions (Hansson and Lagerkvist, 2015; Hansson, Manevska-Tasevska and Asmild, 2020). Furthermore, the decision to participate in voluntary agri-environmental payment schemes can be driven by natural production conditions, resulting in different input and output levels between adopters and non-adopters of voluntary agri-environmental programmes (Finger and El Benni, 2013). To reduce the risk of claiming inefficient production, we take voluntary agri-environmental and animal welfare direct payments into account when specifying the output of farms. Furthermore, to differentiate between production technologies in our farm performance analysis, we account for different farm characteristics, including location and stabling system. Switching patterns are analysed to identify potential improvements in farm performance through adaptation to or adoption of more productive technologies.

The existing literature addresses the issue of production heterogeneity by classifying the sample *ex ante* into groups based on *a priori* knowledge or informed assumptions about differences in technology. Frontier functions are then estimated in the second step for the homogeneous groups of firms that are assumed to share the same production technology. For instance, farms are divided according to their output specialisation (e.g. Asmild, Baležentis and Hougaard, 2016; Rasmussen, 2010; Renner, Glauben and Hockmann, 2014), location (e.g. Alem *et al.*, 2019; Vigani and Dwyer, 2020), organic and conventional production systems (Kumbhakar, Tsionas and Sipiläinen, 2009; Lansink, Kyösti and Bäckman, 2002; Tzouvelekas, Pantzios and Fotopoulos, 2001) or by applying cluster analysis on several intensification characteristics (Alvarez *et al.*, 2008). However, besides the question of choosing the appropriate grouping criteria, this approach does not allow researchers to identify how many different technologies exist within the investigated sector. Moreover, some relevant technological characteristics might not be observable in the sample. Thus, such *a priori* classifications using some exogenous sample criteria conducted *ex ante* might be arbitrary, incomplete and lacking in convincing statistical foundation. Furthermore, by applying the two-stage procedure, i.e. grouping farms first and estimating frontier functions for each group, information on the relationship between inputs and outputs from the second stage (production technology estimation) is neglected in the *ex ante* classification.

Due to the increased use of panel data in efficiency analysis, different models allowing the capturing of latent (unobserved) heterogeneity were developed within the framework of stochastic frontier analysis (see e.g. Greene, 2005; Kumbhakar *et al.*, 2020).[1] Some applications in agriculture have shown a strong impact of the chosen approach on efficiency estimates (see e.g. Abdulai and Tietje, 2007; Balcombe *et al.*, 2006; Kumbhakar, Lien and Hardaker, 2014). However, one drawback of all these models for panel data is that they treat the unobserved heterogeneity as a constant (either as a fixed effect or as part of the error term). The remaining parameters of the estimated production frontier function are usually considered being constant over all firms. This assumption is too strict and might be inappropriate if the sample of farms is heterogeneous in terms of production-technology-determining factors and conditions. In such a case, the estimated parameters of a single production frontier are likely to be biased because it is highly unlikely that the 'true' technology is represented by a single technology for the whole sample (Orea and Kumbhakar, 2004).

This article contributes to the existing agricultural economics literature by applying a latent class stochastic frontier model (LCSFM) using a set of farm characteristics including those clearly related to the participation in an agri-environmental programme to separate the sample into multiple technological classes and estimate the parameters of the individual frontier functions (Alvarez and Del Corral, 2010; Alvarez and Arias, 2015; Baráth and Fertő, 2015; Cillero *et al.*, 2019; Kellermann and Salhofer, 2014; Sauer and Morrison Paul, 2013). By using a simultaneous (one-step) approach, technological groups are determined not only according to different separating criteria but also by considering production relationships reflected in the estimated production frontiers. With this approach, each farm is assigned to a particular technological group (latent class) according to the estimated class membership probability. Moreover, using a novel split-panel specification of the LCSFM (Alvarez and Arias, 2015), we relax the strict assumption of constant production technology and allow farms to switch between latent classes over time. This modification induces additional flexibility in the LCSFM, which can be relevant when evaluating farms over a long period (our survey covers 11 years of observations). Moreover, using this extension, we can thus analyse the potential for further farm performance improvements in the Swiss dairy sector, arising from adapting to more productive technologies. By considering heterogeneous technologies within the same sector and changes over time, we contribute to the existing empirical analyses of the economic performance of Swiss dairy farms (Bokusheva, Kumbhakar and Lehmann, 2012; Ferjani, 2009; Hoop *et al.*, 2014; Jan, Lips and Dumondel, 2010, 2012a; Mamardashvili, Bokusheva and Schmid, 2014).

By comparing the maximum potential output level that each farm can produce with the observed input bundle using the given technology and

1 Starting from the conventional fixed-effects and random-effects models developed by Pitt and Lee (1981) and Schmidt and Sickles (1984) within stochastic frontier analysis, more recent approaches attempt to separate persistent and time-varying inefficiency components from firm-specific effects that capture the heterogeneity between individual firms (for a review see e.g. Kumbhakar, Parmeter and Zelenyuk, 2020).

the alternative technology, the following research questions are answered: (i) Which group of farms applies what kind of technology more efficiently? (ii) Which technology dominates the other in terms of a higher output level that can be produced for a given set of inputs? (iii) In how far, to what extent and with what consequences do single farms switch production technologies over time? Based on these results, we draw policy-relevant conclusions on the interlinkages between voluntary agri-environmental programmes and farm performance.

The remaining article is structured as follows: In the next section (Section 2), we explain why linkages between agri-environmental programmes and production technologies need to be considered in performance analysis. In Section 3, we outline the LCSFM and describe how the proposed split-panel specification can be used to analyse efficiency, differences in productivity, and switching patterns. In Section 4, we present the empirical model and the data, followed by the presentation and discussion of the results in Section 5. In Section 6, we provide a summary of the main findings including some policy implications.

2. Interlinkages between agri-environmental programmes and production technologies

Besides ensuring farmers' incomes, agricultural policy pursues various objectives linked to specific environmental goals, and measures have become increasingly targeted and tailored over time. Direct payments play a decisive role in incentivising certain types of farmers' behaviour including the provision of ecosystem services and animal welfare (Finger and El Benni, 2021).

In Switzerland and over the period considered in this study, the cross-compliance-based direct payment scheme distinguished between general direct payments and ecological direct payments[2] that were paid off per hectare agricultural land or per animal unit (El Benni and Lehmann, 2010; Mann, 2008). General direct payments replaced previous price and market support measures that aimed to maintain farm incomes at appropriate levels, while at the same time ensuring food supply, maintaining the landscape, and helping to preserve the social structure in rural areas. These payments also include payments compensating farmers for adverse production conditions in the hilly and mountainous regions and are comparable to the area-based Less Favoured Area Payments of the EU's Common Agricultural Policy. About 98 per cent of all Swiss farmers received general direct payments in the period 2003–2013. Ecological direct payments compensated farmers who voluntarily, and in addition to the cross-compliance requirements, provided ecological compensation areas, eco-quality such as the networking of biologically valuable habitats and

2 To allow for better readability and following the wording of Swiss agricultural policy, we use the term 'ecological direct payments' to describe direct payments provided for agri-environmental services and animal welfare measures.

extensively produced crops. Furthermore, farmers could voluntarily participate in animal welfare programmes, e.g. by using animal-friendly stabling systems and keeping livestock with regular outdoor exercise. These payments made up about one-sixth of the total direct payment budget, with most of it given to farmers implementing animal welfare measures and those providing ecological compensation areas.

Even though direct payments may target different goals, they can affect farms' efficiency in various ways, which makes the investigation of possible interlinkages between subsidies and farm performance an empirical one (Kumbhakar and Lien, 2010; Minviel and Latruffe, 2017; Zhu and Lansink, 2010). For instance, the provision of animal welfare may require additional inputs such as the investment in free-stall housing required for direct payments under a specific programme to which Swiss farmers can subscribe voluntarily. The provision of ecological services may require less labour as compared to more intensive production methods such as in the case of the provision of extensive and low-intensity meadows that are targeted by another voluntary agri-environmental programme. In case of voluntary direct payment programmes, farmers decide to produce these non-marketable goods and receive an additional governmental payment, i.e. price, for these services. Because the provision of these services requires the adaptation of input use, the farms' productivity and efficiency can be affected. Furthermore, the choice for the provision of environmental services and animal welfare may lead to inefficient resource allocation decisions, i.e. farms can be rationally inefficient (Bogetoft and Hougaard, 2003). More precisely, by producing according to animal welfare standards farmers are not pushing their animals towards their maximal productivity and, from an efficiency point of view, overconsume certain production factors (Hansson, Manevska-Tasevska and Asmild, 2020; Henningsen *et al.*, 2018; Lagerkvist *et al.*, 2011). Furthermore, the compliance with agri-environmental programmes also depends on the farm's location. Economic factors were found to play a key role in farmers' decision to self-select into voluntary agri-environmental programmes (Lastra-Bravo *et al.*, 2015; Pavlis *et al.*, 2016). Moreover, programme compliance costs are negatively correlated with production intensity, which, in turn, strongly depends on the natural production conditions, with farmers located on marginal land being more likely to adopt agri-environmental measures (e.g. Finger and El Benni, 2013; Mack and Huber, 2017; Mack, Ritzel and Jan, 2020).

The self-selection into different direct payment programmes, together with the highly different natural production conditions specific to the Alpine countries, leads to significant variation across dairy farming systems and production technologies. When analysing productivity and efficiency of such a heterogeneous farming sector, particular attention must be paid to distinguishing between the differentials in productivity resulting from using different production technologies including resource allocation decisions related to environmental and animal welfare programmes and those resulting from inefficient management practices. Not considering voluntary direct payment programmes and heterogeneity resulting from differences in local economic and natural conditions in efficiency and productivity analysis may produce misleading results.

3. Methodology

3.1. The LCSFM for panel data

To account for heterogeneous production technologies, we apply an LCSFM that combines a stochastic frontier approach with a latent class model, also known as finite mixture model (Greene, 2005). It assumes that there is a finite number of structures (classes) underlying the data, but the true distribution of farms among latent classes in not known to the researcher. Following Orea and Kumbhakar (2004) and Alvarez and Del Corral (2010), we reformulate the standard stochastic production frontier (log-linear formulation) as follows:

$$\ln y_{it} = \ln f(x_{it})\big|_j + \upsilon_{it}\big|_j - u_{it}\big|_j \tag{1}$$

where y_{it} is the observed output of the farm i in period t and x_{it} is the observed vector of inputs. Following the standard practice in the frontier literature, υ_{it} is defined as a normally distributed random term with a mean of zero and constant variance σ_ν^2 and u_{it} is a half-normally distributed inefficiency term, added to the production function to accommodate for technical inefficiency. The vertical bar means that there are different models for each latent class j. The latent class model estimator delivers different parameters for each of the identified (latent) classes.[3]

After specification of the conditional likelihood function (LF) for each farm i at time t belonging to class j, the LF for each farm i is obtained as a weighted average of its likelihood functions for each group j, using the prior probabilities of class j membership as weights (Alvarez and Del Corral, 2010):

$$LF_i = \sum_{J=1}^{J} LF_{ij} P_{ij}. \tag{2}$$

The prior probabilities of class membership P_{ij} are parameterised by applying a multinomial logit specification:

$$P_{ij} = \frac{\exp(\delta_j q_i)}{\sum_{J=1}^{J} \exp(\delta_j q_i)} \tag{3}$$

where q_i is a vector of separating variables, defined as farm-specific characteristics that reflect differences in technologies by farms, and δ_j is the associated vector of parameters to be estimated. In the multinomial logit model, one class is chosen as a reference by setting all parameters δ_j for this class equal to zero.

3 Although LCSFM takes into account endogeneity of technological choice with respect to inefficiency (Kumbhakar, Tsionas and Sipiläinen, 2009), it does not consider other sources of endogeneity in inputs that might be present in our application.

A positive sign for the coefficient δ_j indicates that the probability of membership in the particular class increases with the increasing value of the specific variable.

The estimated parameters can then be used to compute the conditional posterior class probabilities for each farm:

$$Pr_{ij} = \frac{LF_{ij}P_{ij}}{\sum_{J=1}^{J} LF_{ij}P_{ij}}. \tag{4}$$

Note that posterior probabilities of class membership depend not only on separating variables but also on all the parameters of the stochastic frontier function. Hence, if no separating variables are included in the model, the classes are built using the goodness of fit for each estimated frontier (Orea and Kumbhakar, 2004). As a result, each farm is assigned to a particular class according to the estimated probabilities of class membership, considering the homogeneity among farms within a group in terms of technological parameters. The advantage of the LCSFM is that both the technology and the probability of particular group membership are estimated simultaneously (in one step) and all observations in the sample are used to estimate the underlying technology for each class (Orea and Kumbhakar, 2004).

Because the true number of latent classes cannot be estimated within the model estimation itself, it must be determined by the researcher prior to the estimation. Orea and Kumbhakar (2004) and Greene (2005) suggest using the Akaike information criteria (AIC) and Bayesian information criteria (BIC) with a penalty imposed to the number of parameters to assess the statistically preferred number of classes.[4] The model with the lowest values of AIC or BIC determines the optimum number of classes, given the sample, model parameterisation and estimator chosen.

3.2. Modelling switching between classes

Most of the relevant literature applies the LCSFM with constant (time-invariant) probabilities for the individual class membership, which results from the panel specification of these models (Cillero *et al.*, 2019; Greene, 2005; Kellermann and Salhofer, 2014; Kumbhakar and Tsionas, 2011). However, it is very restrictive and not realistic to assume that a farm is not able to adopt a new technology, especially when observing farms during a longer period. Sauer and Morrison Paul (2013) abandoned this assumption by neglecting the panel structure and considering each observation as a different farm. They estimated the restricted pooled latent class model in the first step to calculate the time-varying class probabilities, allowing farms to change the production technology any time. However, neglecting the panel data structure

4 AIC and BIC are computed using the following formulas: $C = -2\ln LF + 2p$, $BIC = -2\ln LF + p\ln n$, where *LF* is the log-likelihood function of the model with a given number of latent classes, *p* is the number of parameters and *n* is the number of observations.

might lead to biased estimates.[5] Furthermore, some input and output outliers might falsely be considered as changes of production technology (Agrell and Brea-Solís, 2017). Alvarez and Arias (2015) applied a specification of the LCSFM, allowing switching between technological classes by splitting the original balanced panel into two periods. Estimating a single latent class model for this split panel leads to a constant probability of class membership within the two subperiods, which can however be different in the two subperiods for the same farm.

We follow Alvarez and Arias (2015) and split the panel data set (in our case, it is an unbalanced panel) prior to the estimation of the LCSFM. However, we divide observations of each farm in the considered period into two (equal) subperiods in the middle, instead of setting one common breakpoint for the entire sample. Thus, each farm is treated as a different farm in the second subperiod and can switch the class once during the survey period. For example, a farm with 8 years of observation can belong to class 1 in the first 4 years and change to class 2 in the last 4 years or stay in class 1 for the entire observed period.

This modification induces additional flexibility in the LCSFM, which can be relevant when evaluating farms over a long period (our survey covers 11 years of observations). Moreover, it provides an extension of the performance evaluation by analysing the impacts of technology choice and change.

3.3. Estimating efficiency and relative productivity from the LCSFM

In contrast to standard SFM with a common frontier function for every farm, the LCSFM provides estimates for as many frontiers as the number of latent classes identified. An output-oriented index of technical efficiency (TE) is calculated as the ratio of the observed output y_{it} to the maximum feasible output according to the corresponding frontier of class j (reference technology) and can be computed as follows:

$$TE_{it}\big|_j = \exp\left(-u_{it}\big|_j\right). \tag{5}$$

We apply the standard approach and estimate technical efficiency with respect to the most likely frontier (the one with the highest posterior probability of class membership).[6] For interpretation, note that efficiency levels of single farms can only meaningfully be compared with the class-specific reference technology but not across different technology classes. Thus, it may be the case that a farm has a high efficiency level with reference to its own class

5 However, being aware of this likely bias, Sauer and Morrison Paul (2013) presented panel estimates for the separated technologies as robustness checks.

6 An alternative approach would be to calculate a weighted average of efficiency levels with respect to all the frontiers, using the posterior probabilities of the corresponding technological class as weights. Orea and Kumbhakar (2004) argue that both methods lead to almost identical results if the estimated posterior probabilities are high (i.e. uncertainty in the class assignment is low).

frontier, but the class frontier itself is located below the frontier of another technological class. It is therefore possible to analyse efficiency differences between farms belonging to the same technological class as well as productivity differences across technologies driven by factors that cannot be influenced by the farm operator.

Productivity is analysed by comparing the predicted output of farms belonging to a particular class (by using the estimated coefficients of the corresponding production technology) with the predicted output calculated using the technology parameters of the alternative class for given input quantities (Alvarez and Del Corral, 2010; Sauer and Morrison Paul, 2013). However, comparing only the average productivity differentials only means that one technology is locally above the others. It is possible that two frontiers cross.

If the predicted output ratio (productivity ratio) is greater than one for all farms of the class, we can conclude that they use the more productive technology. The number of farms in the class with the higher predicted output is usually used in the literature to evaluate whether one technology dominates the other (Alvarez and Del Corral, 2010; Alvarez and Arias, 2015).[7] Note that this measure is free of random noise and free of individual inefficiency, and it controls for input usage (Kumbhakar, Tsionas and Sipiläinen, 2009).

The approach used in the current study to compare economic performance of farms belonging to different technological groups is similar to the inter-firm efficiency measurement proposed by Lansink *et al.* (2001) and the relative productivity measurement applied by Zhu and Milan Demeter (2012). They measure performance relative to the best available technology in the specific firm by defining the 'best-practice frontier' among the considered groups of firms. Within a metafrontier framework, the 'technology gap ratio' (Battese, Prasada Rao and O'Donnell, 2004) and the 'metatechnology ratio' (O'Donnell, Rao and Battese, 2008) are similar concepts measuring the ratio of the potential output of the frontier function for the *j*th group to the potential output that is defined by the metafrontier function. In the present article, we estimate these ratios with respect to the 'most/more productive technology' instead of the metafrontier.

Analogous to the efficiency with respect to the metafrontier function, we can further calculate the overall efficiency of the farm by multiplying technical efficiency calculated based on the corresponding frontier function with the productivity ratio related to the more productive technological class. Using this measure, we can evaluate overall performance of farms and potential productivity increase reflecting both management improvement and adoption of the more productive technology.

7 Alvarez and Arias (2014) use the term 'efficiency of technology' to explain the differentials in productivity levels of technological classes.

4. Empirical approach and data

4.1. Sample

We use data of 1,513 dairy farms[8] that participated in the yearly panel survey of the Swiss Farm Accountancy Data Network (FADN) collected by Agroscope for the period from 2003 to 2013 (Hoop and Schmid, 2014). Only farms with at least 4 years of observations are considered in order to properly estimate the split-panel model specification. The unbalanced panel data set with a total of 11,184 observations contains detailed farm-level information on production and costs, complemented by additional data on labour input, land use and livestock units.

Dairy farms in our sample have on average 20 cows and cultivate about 21 hectares of agricultural land. They are located in regions with different climatic and topographic conditions: 40 per cent produce in mountain regions with unfavourable production conditions,[9] 20 per cent in hilly and 40 per cent in valley regions. Although the data set contains only farms specialised in dairying according to the Swiss FADN typology (Jan, Lips and Dumondel, 2012a), highly specialised farms are rarely found in Switzerland. Farms are characterised by considerable variation with respect to size, product mix, quality of inputs, natural environment conditions and other attributes.

4.2. Output specification

Because the majority of Swiss dairy farms generate income from several activities, we use the aggregated output per farm rather than physical milk quantity produced to estimate the production technology of Swiss dairy farms. For instance, in our sample, milk and other dairy products make up a large share (on average 75 per cent) of the average farm's revenue from agricultural production, but one-fifth of the farms in the data sample generate more than 40 per cent of their revenue from other agricultural commodities (including other animal products and plant production). Moreover, because other activities, closely related to agriculture (e.g. subcontracting work, renting out land, machinery or buildings), are important sources of farm income and require additional input usage, the revenues from these services are considered as an output. With regard to the consideration of direct payments in the production function, we follow the argumentation in Section 2 and include subsidies from the participation in voluntary ecological direct payment programmes in addition to the previously defined output set to approximate the ecological services provided by the farm (see for a similar approach Jan, Lips and Dumondel, 2012a).

In summary, we define the aggregated output as the total farm revenue from agricultural production, supplemented by revenues from activities closely

8 Farm is defined as specialised in dairy according to the Swiss FADN typology (Jan, Lips and Dumondel, 2012a) based on the share of (dairy) cows in the entire cattle population.

9 Mountain region includes mountain agricultural zones 2, 3 and 4 as defined by the Swiss Federal Office for Agriculture (FOAG, 2019).

related to agriculture and by ecological direct payments. Deflation is performed at the level of each single output (i.e. at every single revenue position) that makes up the aggregate output to obtain the accurate volume measures by considering the composition of products at the farm level.[10] Corresponding price indices for agricultural products and the consumer price index (used to deflate revenues from non-agricultural activities and direct payments) are provided by the Swiss Federal Statistical Office.

4.3. Input specification

We consider four essential inputs: land, labour, capital and materials. Land input is defined as total utilised agricultural area, measured in hectares.[11] Total labour input includes both family and hired labour involved in farming and farm-related activities and is measured in standardised working days (SWDs).[12] Capital is measured by the depreciation value of machines and buildings, supplemented by the depreciation in the value of dairy livestock (in Swiss francs). Depreciation is routinely used in production analysis as proxy for the flow of capital services. However, instead of using depreciation values reported in a firm's financial statements (which might be influenced by the income tax saving strategies), we use the depreciation value from the standardised 'farm accounts' obliged for the farms that participated in the Swiss FADN survey. This system requires uniform straight-line depreciation rules for all fixed assets. Therefore, the calculated depreciation value reflects the quantity of capital each farm uses each year. Depreciation is deflated at the single asset positions by the corresponding price indices for means of agricultural production (for machines, buildings and equipment). The depreciation of livestock is calculated by dividing the annual average book value of dairy livestock (which is evaluated at the corresponding guide price) by the average productive lifetime of a dairy cow in Switzerland (3.2 years[13]). Materials defined as total costs of intermediate inputs include purchased feed, fertiliser, seed, veterinary costs and other material costs (in Swiss francs) and are deflated at the level of each single cost position by the corresponding price indices for means of agricultural production, originating from official Swiss agricultural statistics (Swiss Federal Office of Agriculture and Swiss Farmers' Association).

10 See Jan, Lips and Dumondel (2012a) for the detailed description and discussion of the applied deflation method.

11 Because dairy farms use 94 per cent of the total land for pasture, we do not consider differences in land use. Land quality differences are partially considered by using region as separating variable (see Section 4.4).

12 The effective working days and hours in farming are standardised with respect to a 'normal' 10-hour working day.

13 The average productive time of dairy cows in Switzerland is calculated based on a culling rate of 0.31 calculated by Gazzarin *et al.* (2005).

4.4. Separating variables

Additional separating variables are considered for the LCSFM, allowing us to determine the individual class probability and to improve the classification of technology (Sauer and Morrison Paul, 2013). Empirical applications of latent class models for different agricultural production systems most frequently use indicators measuring the degree of intensification as part of the vector of separating variables (Alvarez and Del Corral, 2010; Alvarez and Arias, 2014; Kellermann and Salhofer, 2014; Orea, Pérez and Roibás, 2015; Sauer and Morrison Paul, 2013). Because differences in climatic conditions among regions may affect the choices made in relation to the use of available technologies, several studies use location as an additional covariate of the class separating process (Alvarez and Del Corral, 2010; Cillero *et al.*, 2019; Kumbhakar, Tsionas and Sipiläinen, 2009). Some researchers include indicators of the degree of specialisation or diversification of production (Cillero *et al.*, 2019; Sauer and Morrison Paul, 2013) or size of farm operations (Orea, Pérez and Roibás, 2015).

The following four variables reflecting differences in dairying production systems in Switzerland are available in the data set: (i) the livestock density, defined as livestock units per hectare, as an indicator of production intensity;[14] (ii) a dummy variable indicating a location in the mountainous region to consider differences in natural production conditions; (iii) a dummy variable indicating whether a tie-up barn or free-stall housing system is used and (iv) a dummy variable for silage-free production influencing both the input use and the milk price received (and consequently the farm revenues).[15] Free-stall housing indicates the farms' compliance with the animal welfare programme to which Swiss farmers can voluntarily subscribe. Silage-free production indicates that the farm produces milk for the production of raw milk cheese, making up more than 40 per cent of the total Swiss milk production (Finger, Listorti and Tonini, 2017).

Table 1 summarises the descriptive statistics of the variables considered for the LCSFM specification, including one aggregated output, four inputs and four separating variables. A significant change in average values over time and a large degree of heterogeneity between farms (as indicated by the variables' standard deviations) underline the need to consider heterogeneity within the model for an appropriate estimation of productivity and efficiency across the sample of dairy farms.

14 In this study, we use the definition of 'livestock unit' and 'livestock density' according to the Eurostat glossary (https://ec.europa.eu/eurostat/statistics-explained).

15 We have tested whether some other variables (labour input per cow, share of subsidies and off-farm share) deliver useful information in classifying the sample and found, based on different test statistics (LF, AIC and BIC), that the model with the four selected separating variables was the preferable specification.

Table 1. Descriptive statistics and definitions of variables used in LCSFM

	Definition	Mean 2003	Mean 2013
Output	Revenue from agricultural outputs, agriculture-related services and ecological direct payments (CHF)	135,655 (72,678)	169,260 (101,845)
Input variables			
Land	Utilised agricultural area (hectare)	19.3 (8.4)	23.4 (11.2)
Labour	Family and hired labour (SWD)	472 (153)	492 (154)
Capital	Depreciation of buildings, machines and dairy livestock (CHF)	44,649 (35,220)	47,880 (25,128)
Materials	Cost of intermediate inputs (CHF)	83,338 (47,855)	109,652 (65,638)
Separating variables			
Livestock density	Livestock units per land area (LU per hectare)	1.3 (0.4)	1.4 (0.5)
Mountain region	Dummy variable with a value of 1 if farm is located the mountainous region (0 otherwise)	0.40	0.42
Stall system	Dummy variable with a value of 1 for farms with tie-up barn and 0 for the free-stall system	0.80	0.70
Silage-free production	Dummy variable with a value of 1 for silage-free production and 0 otherwise	0.36	0.39

Note: Standard deviations in parentheses. CHF, Swiss franc; LU, livestock unit according to the Eurostat definition; SWD, standardised working day.

4.5. Empirical model

The stochastic production frontier function is estimated using the flexible translog specification for one output and different inputs (normalised by their geometric means):

$$\ln y_{it} = \beta_0|_j + \beta_t|_j t + \frac{1}{2}\beta_{tt}|_j t^2 + \sum_{k=1}^{K}\beta_k|_j \ln x_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K}\beta_{kk}|_j \ln x_{kit}\ln x_{lit} + \sum_{k=1}^{K}\beta_{kt}|_j \ln x_{kit} t \quad (6)$$

where the β values are parameters to be estimated. We include the time trend variable t and its interactions with inputs to capture (non-neutral) technical change. The stochastic part of the model is decomposed according to equation (2) into a noise term υ_{it} and a time-varying inefficiency term u_{it}. The estimation of parameters is carried out using the econometric software NLOGIT 6.0 (Greene, 2012).

5. Results and discussion

5.1. Identification of three production technology classes

Based on the estimated posterior class probabilities, three distinct technological classes of dairy farms can be identified in Switzerland in the investigated period: Class 1 'most productive class', class 2 'average productive class' and class 3 'least productive class'. The LCSFM with three classes is preferred over other specifications because of the lowest AIC and BIC values.[16] Average values of posterior probabilities are quite high (0.948, 0.927 and 0.953 for classes 1, 2 and 3, respectively), indicating that the estimated classification of farms in the particular technological class is statistically robust. The estimates for the prior probability function are shown in Table 2. All four separating variables have a significant impact on the probability of belonging to a certain class (the 'average productive class' is the reference category) at farm level. Hence, the considered farm characteristics provide useful information for classifying the individual farms in the sample.

As a robustness check, we compared the model with and without separating variables and found that 82 per cent of the farms are assigned to the same classes, indicating that the most important information for technology classification comes from the production relationships reflected in the estimated production frontiers. Further sensitivity tests show that including location and livestock density as covariates of the probability function also

16 The LCSFM with four classes failed to converge. Following Orea and Kumbhakar (2004), we interpret this as evidence that a model with four classes is overspecified. We have tried out many different specifications of our model and in each case we end up with three classes. If we tried the simplest specification, the LCSFM estimation with four classes was possible, but according to the selection criteria, it was not better than the model with three classes.

Table 2. Coefficients and t-ratios of the latent class prior probability function

	Class 1 'most productive'		Class 3 'least productive'	
	Coefficient	*t*-ratio	Coefficient	*t*-ratio
Constant	−1.74	−6.88***	0.53	1.78*
Livestock density	1.29	8.79***	−2.04	−9.44***
Mountain region	−1.35	−9.35***	1.65	12.61***
Stall system	−0.57	−4.82***	0.75	4.75***
Silage-free production	0.63	5.89***	−0.56	−4.46***

Note: Class 2 'average productive class' is the reference category. * and *** indicate statistical significance at the 10 per cent and 1 per cent levels, respectively.

contributes largely to the separation between production technologies. Adding the stall system and silage-free production enhances the results by increasing posterior probability but does not lead to huge changes in farms between productivity classes. Thus, the self-selection into voluntary agri-environmental programmes occurs to be strongly correlated to the natural production conditions, and these conditions restrict the set of production technologies that are available to farmers.

The results (Table 2) show that, compared with the average productive class, farmers of the most productive class have higher livestock density, are less likely located in the mountain regions, more likely have free-stall barns entitling them to participate in the animal welfare programme and are more likely to produce silage-free milk used for raw milk cheese production. In contrast, farmers of the least productive class are more likely located in the mountain regions, produce comparably extensively and are more likely to use tie-up barns and to produce drinking milk as compared with average productive class of farmers.

We present in Table 3 the first-order output elasticities at the sample mean of each technological class. They reflect the contribution of inputs, scale elasticities and technical change. Elasticities are also calculated at each data point to check whether the estimated production functions are well-behaved according to regularity conditions. It shows that partial production elasticities are positive in all three classes at the sample mean and for almost all observations. Hence, the monotonicity condition is violated only at a few data points.[17] We do not report the parameter estimates of the LCSFM due to space limitations and limited interpretability of the coefficients (you can find them in Appendix).[18]

Some differences are observed with respect to the marginal contribution of different inputs among the technological classes. Materials (including costs of purchased feed and other intermediate inputs) are the most important input

17 We also checked the curvature of the estimated translog functions for each class, which were quasi-concave at the sample mean (tolerance level = 0.01).

18 Note that the first-order coefficients of the LCSFM presented in the Appendix are calculated at the geometric mean of the entire sample and therefore differ from the elasticities of the three classes, since the latter are evaluated at their corresponding sample means, not at the mean of the entire sample.

Table 3. Output elasticities, technical change and scale elasticity calculated at the sample mean of the corresponding class and share of positive observations

	Class 1 'most productive'		Class 2 'average productive'		Class 3 'least productive'	
	Estimate	Obs. > 0	Estimate	Obs. > 0	Estimate	Obs. > 0
Land	0.179 (0.010)	98%	0.222 (0.011)	97%	0.218 (0.013)	99%
Labour	0.099 (0.010)	99%	0.099 (0.009)	100%	0.114 (0.012)	100%
Capital	0.233 (0.012)	100%	0.218 (0.013)	100%	0.240 (0.015)	100%
Materials	0.539 (0.012)	100%	0.535 (0.013)	100%	0.548 (0.013)	100%
Technical change	0.002 (0.001)	65%	−0.003 (0.001)	24%	−0.008 (0.001)	7%
Scale elasticity	1.050 (0.011)		1.075 (0.011)		1.120 (0.013)	

Note: Standard errors in parentheses. Output elasticities with respect to all four inputs are significantly different from zero at the 0.01 significance level in all three classes; mean scale elasticities in all three classes are significantly different from one.

for all three production technologies with very little differences in elasticities between classes.[19] This finding is in line with other studies (e.g. Cillero *et al.*, 2019; Kellermann and Salhofer, 2014). More precisely, a 1 per cent increase in the use of materials leads on average to a 0.5 per cent increase in output, irrespective of the technology used. For the most productive class 1 farms, output is relatively less responsive to land as compared with the other two classes. Farms in the least productive class 3 obtain the largest returns to land when compared with the other two classes.

Some differences can be observed with respect to returns to scale, calculated as the sum of the output elasticities with respect to all four inputs (Table 3; Figure 1). Farms in all three classes operate on average under increasing returns to scale, meaning that they should still be able to improve economic performance by adjusting their size. The most productive farms in class 1 could increase their output by 1.05 per cent, the average productive farms in class 2 even by 1.075 per cent and the least productive farms in class 3 even by 1.12 per cent based on a 1 per cent increase in all inputs. This result is not surprising considering the small-structured Swiss dairy production (see Table 1).

Technical change is found to be small for the production technology of the most productive class and even slightly negative for the average and least productive class, whereby it is not significantly different from zero. Alvarez and Del Corral (2010) also found low levels of technical change of between 0.004 for extensive and 0.013 for intensive dairy farms in Spain, and Kumbakhar *et al*. (2009) found negative technical change for Finnish dairy farms, which they related to changes in price and subsidy levels and weather conditions. Furthermore, the estimated technical change might be underestimated because only economic resources and outputs are considered in the estimation of the production technology (Jan, Lips and Dumondel, 2010; Jan *et al.*, 2012b). The role of non-monetary (agri-environmental) outputs is only partially captured by including the ecological direct payment subsidies as part of the farm output.

Table 4 provides descriptive statistics for some characteristics of the farms assigned to the three technological classes based on the estimated probabilities of individual class membership. Considering the results from Table 4 in combination with estimated elasticities from Table 3, we can examine differences between the identified groups of farms.

The most productive class 1 comprises significantly larger farms (in terms of both output and number of cows) using a more intensive technology (in terms of livestock density) with high milk yield (6,756 kg milk per cow) and a comparably high labour productivity (420 CHF/day). Production intensities (livestock units per hectare) are already high and can hardly be increased without a growth in farm size (i.e. hectares land cultivated) because cross-compliance obligations restrict production intensities. Thus, for farmers in this class, land is likely the restricting factor to further increase output levels, and structural change would be needed to allow for further farm growth.

19 Due to convergence problems in the estimation procedure, it was not possible to divide materials further into individual components.

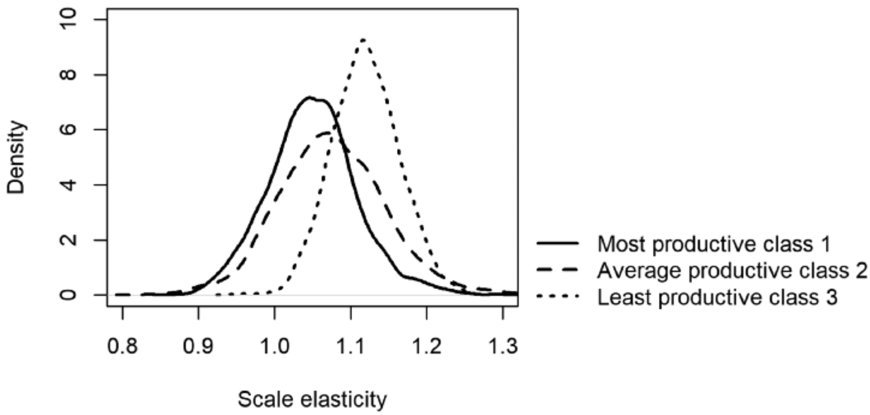

Fig. 1. Kernel density of scale elasticities by classes.

Table 4. Mean farm characteristics of identified technological classes

	Class 1 'most productive'	Class 2 'average productive'	Class 3 'least productive'
Observations	3,601	4,673	2,910
Output (CHF)	212,372	148,987	97,096
Milk production (CHF)	128,962	88,264	54,917
Labour per cow (SWD)	22.5	27.6	34.7
Livestock per ha (LU per hectare)	1.6	1.4	1.1
Located in mountain region	0.11	0.38	0.82
Cows	24.7	19.7	14.7
Land (hectare)	20.9	21.6	21.9
Milk yield (kg per cow and year)	6,756	6,238	5,669
Labour productivity (CHF per SWD)	420	298	203
Subsidies' share in total revenue	0.22	0.31	0.44
Share of off-farm income in total family income	0.19	0.28	0.38

Note: Sample means of the presented variables are significantly different between classes at the 0.01 significance level with the exception of land. CHF, Swiss franc; LU, livestock unit; SWD, standardised working day.

The least productive class 3 producers, in contrast, have smaller herds (they have on average 15 cows) and produce extensively with almost only half of the livestock density and low milk yields in comparison with the most productive class 1 farmers but use more labour-intensive technologies. Most of the farms in this class (82 per cent) are located in the mountain regions, their farmers

Table 5. Average predicted output levels ($\hat{y}$) in Swiss francs and corresponding productivity ratios calculated for dairy farms in identified classes using different production technologies

	Class 1 'most productive'	Class 2 'average productive'	Class 3 'least productive'
$\hat{y}_1$ (using technology 1)	216,286	184,284	156,315
$\hat{y}_2$ (using technology 2)	192,277	162,142	136,873
$\hat{y}_3$ (using technology 3)	167,270	139,544	117,222
Productivity ratio $\hat{y}_j/\hat{y}_1$	1.00	0.88	0.75
Productivity ratio $\hat{y}_j/\hat{y}_2$	1.12	1.00	0.86
Productivity ratio $\hat{y}_j/\hat{y}_3$	1.29	1.16	1.00

earn a considerable share of income (one-third) off the farm and governmental subsidies are an important income source. Labour productivity is very low in the least productive class 3, generating less than half the levels of productivity (CHF per annual working unit) as compared with class 1 farmers.

Average productive class 2 producers can be described as being in between both other classes with respect to the characteristics shown in Table 4. However, farm size in hectares shows to be similar across all farm groups.

5.2. Productivity levels of technology classes

To examine the productivity differences between technological classes, we calculate the predicted output of each farm based on different production technologies identified (using the estimated parameters of the three identified latent class models). The predicted values based on the production frontier of the least productive class 3 are lower for all observations in the sample compared with the production frontiers of the other two classes. On the other hand, the production frontier of the most productive class 1 is located above that of the average productive class 2 for almost all farms (with an exception of 0.4 per cent of observations from class 2 with higher predicted output values). Thus, we can consider the technology of class 1 as the 'most productive technology'.

Means of predicted output values ($\hat{y}_j$) for the farms in the classes are reported in Table 5. The productivity ratios in the lower part of the Table 5 show, for the farms in each class, how far the average predicted output is from the potential output level they could realise if they used the alternative technology instead of the technology they currently used technology. These results reveal considerable differences in the productivity levels between the three latent technologies.

Farms in the most productive class 1 can achieve the highest productivity level with the actually implemented technology (technology 1). The average productivity ratio of these farms with respect to the other frontiers is 1.12 and 1.29, which means that they can produce at considerably higher output levels as compared with potential output from using the two alternative technologies. On the other side, if farms from the average or least productive classes 2 and 3 adopted the most productive technology 1, they could potentially produce on

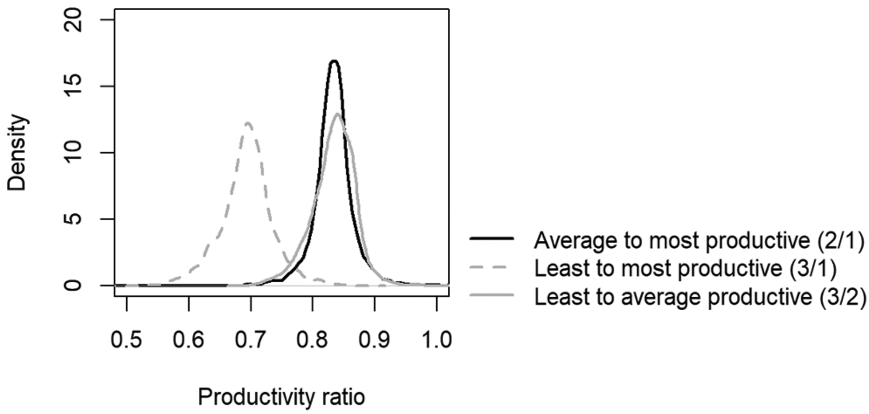

Fig. 2. Kernel density of productivity ratios of farms from the less productive classes 2 and 3 with respect to the more productive reference technology.

average 12 per cent and 25 per cent more output, respectively (as indicated by average productivity ratios of 0.88 and 0.75 for these less productive classes). The gains for farms in the least productive class 3 from a switch to the average productive class 2 technology would induce a 14 per cent increase in output (productivity ratio of 0.86).

In addition to the average values, Figure 2 presents the distribution of productivity differentials of the farms from the average class 2 with respect to the most productive class 1 (solid black line) and from the least productive class 3 with respect to the average and the most productive classes 2 and 1 (solid and dotted grey lines). Even though the results of our study suggest a substantial potential for productivity improvements (20–40 per cent output increase for farms of the technologically least productive class 3 due to adoption of the most productive class 1 technology), it should be kept in mind that switching to a more productive technology might not be possible for all farms in reality. Whereas in some cases extensive investments can be the restrictive factor, technology use is also restricted by natural production conditions that can hardly be influenced by farmers. For instance, least productive class 3 farms are mostly located in mountainous regions where an increase in productivity levels is often not possible because of low availability of grass quantity and quality; thus, the farmers face restricted possibilities for production intensification. A more detailed discussion on change of the technological class can be found in Section 5.4.

Hence, when comparing the performance of farms, it is of outmost importance to consider the differences in productivity resulting from differences in technologies used. Otherwise, productivity differences across farms could wrongly be interpreted as inefficiency resulting from poor management skills (see Section 5.3) even though they are the result of technology choices adapted to local agri-environmental conditions.

Table 6. Average technical efficiency levels calculated for dairy farms in identified classes with reference to different production frontiers

	Class 1 'most productive'	Class 2 'average productive'	Class 3 'least productive'
Efficiency based on common frontier[a]	0.83	0.65	0.50
Efficiency based on own class frontier	0.98	0.96	0.88
Efficiency based on class 1 frontier[b]	–	0.80	0.61
Efficiency based on class 2 frontier[b]	–	–	0.73

[a]Efficiency relative to the common frontier is calculated using a random-effects stochastic frontier model.
[b]Technical efficiency with reference to the own class frontier multiplied with the productivity ratio of the current technology to the more productive technology.

5.3. Technical efficiency

For further performance analysis, we estimate the technical efficiency of each farm with reference to different frontiers (common frontier, own class frontier and 'best-practice frontier') and present average values by latent class in Table 6. As shown in the previous section, the production frontier of class 1 is located above the other two production frontiers. Thus, it can be considered as the 'most productive' technology analogue to the concept of 'metafrontier' or 'best-practice frontier' definitions from the efficiency literature. Using this concept, we can additionally calculate efficiency for each farm with reference to the maximum possible output that can be achieved by efficient use of given inputs and producing with the most productive technology. It is calculated by multiplying the technical efficiency with reference to the own frontier with the productivity ratio of the current technology to the more productive technology, using the results presented in Section 5.2.

First, our results show that technical efficiency is much lower if we do not consider technological heterogeneity between farms and assume that all farms show a common production frontier. According to this calculation, farms from the least productive class 3 could double their output by using the current input levels. However, results of the LCSFM estimation confirm that dairy farms in our sample use different production technologies. As shown in Section 5.2, the frontier of the least productive class 3 is located below the other frontiers, which means that these farms are not able to reach the output levels of the common frontier. Hence, it is not reasonable to estimate efficiency with respect to a single common frontier, from the vantage point of economic theory.

The efficiency scores estimated with respect to the individual frontiers of the corresponding latent technological class are higher. It is an expected result because farms belonging to one class are more homogeneous and thus produce closer to their own production frontier (Alvarez and Del Corral, 2010).

Table 7. Number and share of dairy farms switching the latent class

	Number of farms			Share of farms		
	To class 1	To class 2	To class 3	To class 1	To class 2	To class 3
From 'most productive' class 1	390	72	3	26%	5%	0%
From 'average productive' class 2	107	471	61	7%	31%	4%
From 'least productive' class 3	0	89	320	0%	6%	21%

At current levels of input use and assuming fully efficient use of these inputs, farms in the average productive class 2 could obtain on average a 4 per cent increase in output levels with their current production technology. If they were able to switch to the most productive technology 1, they could even reach a 20 per cent increase in output level. This finding means that technological restriction (and not necessarily lack of management skills) is the major limiting factor of economic performance enhancement. Farms in the least productive class 3 could produce 12 per cent more with their current technology and could obtain a 27 per cent increase after switching to the average productive class 2 technology and even a 39 per cent increase if they were able to adopt the most productive class 1 technology. In the next section, we show how many farms were able to change the class according to our results.

5.4. Switching patterns

The split-panel specification of the LCSFM allows us to analyse the switching patterns of farms, i.e. the change of the production technology over time. In our formulation, we allow each farm to adopt a new technology once during the period. First, we analyse how many farms change the technology and how many remain in the same technological class during the entire data period considered. Second, we analyse differences in some characteristics of farms depending on the adaptation decision.

As shown in Table 7, most dairy farms (78 per cent) do not change the production technology in the period considered. Twenty-six per cent remain in the most productive class 1 throughout the entire period. If farms make a change, they more likely switch to a more productive technology. However, only every fourth farm in the average and least productive classes 2 and 3 has adopted a new technology during the investigated period. The finding that (almost) no farm has switched between the least and most productive classes 3 and 1 suggests that the observed technology use is quite well adapted to local environment-related conditions and that the least productive class 3 farms are hardly able to switch to the production technology used by the most productive class 1 farms.

In Table 8, we compare the performance of farms in terms of technical efficiency before and after switching the technological class. If we compare the management ability of farms belonging to the average productive class 2

Table 8. Comparison of average technical efficiency levels between farms with different switching patterns

	1	1→2	2	2→1	2→3	3	3→2
Subperiod 1 (before switching)	0.983	0.981	0.959	0.969	0.947	0.870	0.922
Subperiod 2 (after switching)	0.983	0.913	0.959	0.981	0.913	0.870	0.947

Note: '1' refers to the farms staying in the most productive class 1; '1→2' refers to the farms switching from the most productive class 1 to the average productive class 2, and so forth.

in subperiod 1 (before switching), we observe higher average technical efficiency levels of farms that were able to change to the most productive class 1 (0.969) as compared with the farms that stayed in the average productive class 2 (0.959) or switched to the least productive class 3 (0.947). A more marked difference can be found between the mean technical efficiency of farms in the least productive class 3. Farms changing to the average productive class 2 are

Table 9. Relative change in mean values of selected farm characteristics from subperiod 1 to subperiod 2 (in %) by groups of farms with different switching patterns

	1	1→2	2	2→1	2→3	3	3→2
Agricultural income (CHF)	5.0	−14.4	−3.4	18.5	−34.9	−9.0	21.6
Working income per family labour unit[a]	8.0	−17.3	0.4	31.5	−40.8	−3.5	28.9
Output (CHF)	8.6	−1.8	6.4	14.6	−5.4	2.3	18.1
Milk production (CHF)	15.3	6.5	11.3	27.4	−0.4	8.2	23.4
Labour per cow (SWD)	−7.0	−3.1	−4.6	−8.2	5.7	−2.2	−4.4
Livestock per hectare (LU per hectare)	3.8	−5.5	2.8	7.3	−2.1	0.4	6.2
Cows	10.2	5.8	7.8	14.4	−0.2	4.9	8.5
Land (hectare)	3.1	6.1	3.0	1.8	1.3	3.2	1.8
Subsidies' share in total revenue[b]	12.6	20.8	9.5	3.3	16.6	5.5	−1.3
Milk yield (kg per cow and year)	1.3	0.8	1.2	4.4	−0.5	0.7	6.7
Labour productivity (CHF per SWD)	5.8	−3.7	4.6	10.5	−10.8	0.0	13.5
Off-farm share[c]	10.5	95.4	19.2	12.9	42.2	24.9	−1.3

[a]Working income per family labour unit is calculated as agricultural income after remuneration of the equity invested by the family and divided by the number of non-remunerated full-time working family members (family labour units).
[b]Portion of the total direct payments in the total farm revenue.
[c]Portion of wage employment, self-employment, remittances and other income such as capital earnings and pensions in total family income.
LU, livestock unit; SWD, standardised working day.

able to produce 5 per cent more output with given inputs using class 3 technology before switching (0.922) as compared with the farms staying in class 3 (0.870). Moreover, they also achieve a quite high efficiency level (0.947) with respect to the new benchmark after adopting the new technology.

As shown in Table 9, farms that stay in the most productive class 1 substantially increase production, labour productivity and income. In contrast, farms that stay in the average productive class 2 and especially farms that stay in least productive class 3 are not able to increase production and productivity levels to such an extent that income can be increased (or at least maintained) throughout the period considered. Remarkable is the increasing share of subsidies with respect to total revenues especially for those farms that switch to a technology with lower productivity (i.e. from the most to the average productive class 1 to class 2 and from the average to the least productive class 2 to class 3). Also, the share of off-farm income increases substantially when farms switch to a less productive class. Across all classes, changes in output and productivity levels are smallest for farmers staying in the least productive class 3 throughout the entire period considered.

The 196 farms that switch to a more productive technology over time (columns '2→1' and '3→2') are able to substantially increase outputs, income levels and labour productivity, while the share of subsidies remains stable (for farmers switching from technology 2 to 1) or even decreases (for farmers switching from technology 3 to 2). These farms produce more intensively over time.

The 133 farms that switch to a lower output technology over time (columns '1→2' and '2→3') increase the share of subsidies in total revenue by more than 15 per cent on average. Incomes and outputs decrease substantially. Labour productivity also decreases, and the share of off-farm income in total revenue increases. Production intensities measured by livestock density slightly decrease but measured by milk yields remain rather stable.

The results presented here are descriptive in nature, and causal relationships between the level of governmental support and class membership can thus not be deduced. Nevertheless, it appears that government support and off-farm income play an important role in Swiss farmers' decision-making, a relationship that is taken up in the agricultural household model and is supported by various empirical studies (see e.g. Brick, 2005). The descriptive statistic shown in Table 9 furthermore indicate a production-technology-driven division in the farming population that might at least partly be explained by local natural production conditions that can hardly be influenced by the management of the farm.

6. Conclusions

When analysing farm performance, it is important to distinguish between productivity differentials resulting from the use of different production technologies and those that are due to inefficient management practices. Using an LCSFM approach for a panel data set of Swiss dairy farms between 2003 and

2013, we analysed the potential effect of several farm characteristics, including the compliance with the requirements of a voluntary agri-environmental programme, to differentiate between heterogeneous production technologies. Furthermore, by using a novel split-panel approach, we allowed farms to switch the technology class once during the observed period, allowing us to analyse technology choice and change.

Our results show that technological restrictions are the major limiting factor of economic performance enhancement, as opposed to an often assumed lack of management skills. Three distinct production technologies were identified among the Swiss sample of dairy farms. Dairy farms belonging to the most productive technological class 1 are more likely located in the valley or hilly regions, produce more intensively in terms of livestock density, more likely choose silage-free milk production and more likely use free-stall systems and are thus eligible for voluntary animal welfare direct payments. Farms of the least productive technology class 3 are more likely located in the mountain regions, produce less intensively and more likely use tie-up barns and produce for the drinking milk market. Although the most important information for technology classification comes from the production relationships reflected in the estimated production frontiers (i.e. unobserved factors), farm location and livestock density contribute additionally to the separation between production technologies.

Even though the results suggest substantial productivity gains when switching from one to the next productive technology, only a few farmers with relatively low technical inefficiency levels were able to realise such technology changes. Technology switching patterns over time show that most dairy farms stay in their technology class during the entire period, and no farm using a least productive class 3 technology switched to the most productive class 1 technology. Thus, technologies used in the different classes seem to be well adapted to local natural production conditions. However, note that the chosen split-panel approach only allows for one switch in the period considered, which is supposed to be reasonably flexible and realistic in the farming context over the considered period of 11 years. The current farm performance analysis could be extended to check for potential improvements of specific inputs or outputs by combing the LCSFM with a multidirectional approach (Asmild *et al.*, 2003; Labajova *et al.*, 2016). Applying the novel approach by Hansson, Manevska-Tasevska and Asmild (2020), we could further test for the existence of rational inefficiency among Swiss dairy farms. Furthermore, our study could be extended by incorporating determinants of inefficiency into the LCSFM and applying some sophisticated modifications dealing with endogeneity issues (Amsler, Prokhorov and Schmidt, 2016; Kumbhakar, Parmeter and Zelenyuk, 2020; Latruffe *et al.*, 2017).

The descriptive analysis of the observed technology switching patterns do not allow claiming causal relationships in the development paths in Swiss dairy farming but may provide first insights for further analysis. Our results indicate two distinctive development paths for Swiss dairy farms: (i) a substantial increase in intensification and output levels (intensification strategy) and (ii) a reduction of farm inputs and outputs and decreasing importance of agriculture for household income (extensification strategy). The few farms that were able to adopt a more productive technology are characterised by relatively small shares of subsidies and off-farm income and by producing less inefficiently than the remaining farms in their class. In contrast, farms switching to a less productive technology, being less efficient and more dependent on direct payments as compared with the other farms from their previous class, show an even higher share of subsidies and off-farm income afterwards. Thus, besides natural production conditions, governmental support and off-farm income may play an important role in the technology choice of farmers and should be analysed in more detail in future research. Technology choice, in turn, is intimately linked to the economic situation of farms, and policymakers must be aware of these interrelations.

When designing measures to increase productivity and efficiency of Swiss dairy farms, policymakers should keep in mind that there are substantial differences in the productivity levels of different technologies across the respective farm population. These differences should not be interpreted as inefficiencies resulting from poor management skills. In fact, within their technology classes, Swiss dairy farms already produce quite efficiently on average with given current technologies. Considering the class averages, the output levels could only be increased by 2–12 per cent due to more efficient input use and by 20–27 per cent due to adoption of the more productive technology. Farm size growth would allow farmers to further increase productivity as shown by positive scale elasticities. Nevertheless, non-tradeable direct payments paid per hectare (being an increasingly important income source) result in land as an immobile input factor in Switzerland, which may suppress technological improvements in the whole dairy sector and prevent improvements in farm performance. The results of this study furthermore show that the participation in voluntary agri-environmental schemes is strongly correlated to the natural production conditions. On the one hand, this linkage means that voluntary programmes are not similarly attractive for all farms and adoption and diffusion of e.g. animal welfare measures across the whole sector is limited by natural production conditions. On the other hand, the results also indicate that voluntary agri-environmental programmes do not necessarily lead to low farm performance. In contrast, Swiss dairy farmers using free-stall systems and thus being eligible for agri-environmental payments are the most productive farmers as compared with farmers using tie-up barns in the mountain regions. Allowing farmers to self-select into agri-environmental measures seems to be a good mechanism with respect to income-related and thus productivity- and efficiency-related goals of agricultural policy. However, if environmental and animal welfare improvements are the main objectives, existing measures and subsidy levels need to be adapted to local natural production conditions to be attractive for farmers from an economical point of view.

Future research could explore in more detail the contribution of different voluntary agri-environmental programmes to the heterogeneity in production technologies because not all programmes need to be correlated to the same natural production conditions. Furthermore, and in view of the fact that e.g. animal welfare provide non-use values to farmers, the interrelations between non-use values and direct payment programmes should be considered in future research. Information on the interlinkages between the participation in voluntary programmes, natural production conditions and farm performance can allow for a more attractive policy programme design. Identifying possible causal relationships between subsidies or off-farm income (or both) and the technology choice of farmers is also of interest for future research.

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Conflict of Interest

The authors declare that they have no conflict of interest.

References

Abdulai, A. and Tietje, H. (2007). Estimating technical efficiency under unobserved heterogeneity with stochastic frontier models: application to northern German dairy farms. *European Review of Agricultural Economics* 34(3): 393–416.

Agrell, P. J. and Brea-Solís, H. (2017). Capturing heterogeneity in electricity distribution operations: a critical review of latent class modelling. *Energy Policy* 104: 361–372.

Alem, H., Lien, G., Hardaker, J. B. and Guttormsen, A. (2019). Regional differences in technical efficiency and technological gap of Norwegian dairy farms: a stochastic metafrontier model. *Applied Economics* 51(4): 409–421.

Alvarez, A., Del Corral, J., Solís, D. and Pérez, J. A. (2008). Does intensification improve the economic efficiency of dairy farms? *Journal of Dairy Science* 91(9): 3693–3698.

Alvarez, A. and Del Corral, J. (2010). Identifying different technologies using a latent class model: extensive versus intensive dairy farms. *European Review of Agricultural Economics* 37(2): 231–250.

Alvarez, A. and Arias, C. (2014). A selection of relevant issues in applied stochastic frontier analysis. *Economics and Business Letters* 3(1): 3–11.

Alvarez, A. and Arias, C. (2015). Effects of switching between production systems in dairy farming. *Bio-Based and Applied Economics* 4(1): 1–16.

Amsler, C., Prokhorov, A. and Schmidt, P. (2016). Endogeneity in stochastic frontier models. *Journal of Econometrics* 190(2): 280–288.

Asmild, M., Hougaard, J. L., Kronborg, D. and Kvist, H. K. (2003). Measuring inefficiency via potential improvements. *Journal of Productivity Analysis* 19: 59–76.

Asmild, M., Baležentis, T. and Hougaard, J. L. (2016). Multi-directional program efficiency: the case of Lithuanian family farms. *Journal of Productivity Analysis* 45(1): 23–33.

Balcombe, K., Fraser, I. and Kim, J. H. (2006). Estimating technical efficiency of Australian dairy farms using alternative frontier methodologies. *Applied Economics* 38(19): 2221–2236.

Baráth, L. and Fertő, I. (2015). Heterogeneous technology, scale of land use and technical efficiency: the case of Hungarian crop farms. *Land Use Policy* 42: 141–150.

Battese, G. E., Prasada Rao, D. S. and O'Donnell, C. J. (2004). A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. *Journal of Productivity Analysis* 21(1): 91–103.

Bogetoft, P. and Hougaard, J. L. (2003). Rational inefficiencies. *Journal of Productivity Analysis* 20: 243–271.
Bokusheva, R., Kumbhakar, S. C. and Lehmann, B. (2012). The effect of environmental regulations on Swiss farm productivity. *International Journal of Production Economics* 136(1): 93–101.
Brick, A. (2005). Review of the empirical literature on factors affecting the supply of off-farm labour. Working Paper No. 105. Galway: Department of Economics, National University of Ireland.
Cillero, M. M., Thorne, F., Wallace, M. and Breen, J. (2019). Technology heterogeneity and policy change in farm-level efficiency analysis: an application to the Irish beef sector. *European Review of Agricultural Economics* 46(2): 193–214.
El Benni, N. and Lehmann, B. (2010). Swiss agricultural policy reform: landscape changes in consequence of national agricultural policy and international pressure. In: J. Primdahl and S. Swaffield (eds), *Globalisation and Agricultural Landscapes—Change Patterns and Policy Trends in Developed Countries*. Cambridge, UK: Cambridge University Press, 73–94.
European Court of Auditors. (2016). *Is the Commission's System for Performance Measurement in Relation to Farmers' Incomes Well Designed and Based on Sound Data?* Luxembourg: Publications Office of the European Union.
Ferjani, A. (2009). The relationship between direct payments and efficiency on Swiss farms. *Agricultural Economics Review* 9(389-2016-23323): 93–102.
Finger, R. and El Benni, N. (2013). Farmers' adoption of extensive wheat production—determinants and implications. *Land Use Policy* 30(1): 206–213.
Finger, R., Listorti, G. and Tonini, A. (2017). The Swiss payment for milk processed into cheese: *ex post* and *ex ante* analysis. *Agricultural Economics* 48(4): 437–448.
Finger, R. and El Benni, N. (2021). Farm income in European agriculture: new perspectives on measurement, development and policies. Considered for publication in this special issue at the *European Review of Agricultural Economics* (this issue).
FOAG. (2019). Landwirtschaftliche Zonen-Verordnung mit Weisungen und Erläuterungen 2019; SR 912.1. https://www.blw.admin.ch/blw/de/home/instrumente/grundlagen-und-querschnittsthemen/landwirtschaftliche-zonen.html (accessed 20 January, 2021).
Gazzarin, C., Amman, H., Schick, M., van Caenegem, L. and Lips, M. (2005). *Milchproduktionssysteme in der Tal- und Hügelregion. Was ist Optimal für die Zukunft?* Tänikon: Agroscope FAT, 16.
Greene, W. (2005). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Econometrics* 126(2): 269–303.
Greene, W. H. (2012). NLOGIT version 5 reference guide. Plainview, NY, 11803.
Hansson, H. and Lagerkvist, C. J. (2015). Identifying use and non-use values of animal welfare: evidence from Swedish dairy agriculture. *Food Policy* 50: 35–42.
Hansson, H., Manevska-Tasevska, G. and Asmild, M. (2020). Rationalising inefficiency in agricultural production—the case of Swedish dairy agriculture. *European Review of Agricultural Economics* 47(1): 1–24.
Henningsen, A., Czekay, T. G., Forkman, B., Lund, M. and Nielsen, A. S. (2018). The relationship between animal welfare and economic performance at farm level: a quantitative study of Danish pig producers. *Journal of Agricultural Economics* 69(1): 142–162.
Hoop, D., Mack, G., Mann, S. and Schmid, D. (2014). On the dynamics of agricultural labour input and their impact on productivity and income: an empirical study of Swiss family farms. *International Journal of Agricultural Management* 3(4): 221–231.
Hoop, D. and Schmid, D. (2014). *Grundlagenbericht 2014: Zentrale Auswertung Von Buchhaltungsdaten*. Ettenhausen: Agroscope INH, 270.

Jan, P., Lips, M. and Dumondel, M. (2010). Technical efficiency of Swiss dairy farms located in the mountain area considering both economic and environmental resources. *Yearbook of Socioeconomics in Agriculture* 3(1): 39–76.

Jan, P., Lips, M. and Dumondel, M. (2012a). Total factor productivity change of Swiss dairy farms in the mountain region in the period 1999 to 2008. *Review of Agricultural and Environmental Studies* 93(3): 273–298.

Jan, P., Dux, D., Lips, M., Alig, M. and Dumondel, M. (2012b). On the link between economic and environmental performance of Swiss dairy farms of the alpine area. *The International Journal of Life Cycle Assessment* 17(6): 706–719.

Kellermann, M. and Salhofer, K. (2014). Dairy farming on permanent grassland: can it keep up? *Journal of Dairy Science* 97(10): 6196–6210.

Kumbhakar, S. C., Tsionas, E. G. and Sipiläinen, T. (2009). Joint estimation of technology choice and technical efficiency: an application to organic and conventional dairy farming. *Journal of Productivity Analysis* 31(3): 151–161.

Kumbhakar, S. C. and Lien, G. (2010). Impact of subsidies on farm productivity and efficiency. In: V. E. Ball, R. Fanfani and L. Gutierez (eds), *The Economic Impact of Public Support to Agriculture, Studies in Productivity and Efficiency*. New York, NY: Springer, 109–124.

Kumbhakar, S. C. and Tsionas, E. G. (2011). Some recent developments in efficiency measurement in stochastic frontier models. *Journal of Probability and Statistics* 2011: 603512.

Kumbhakar, S. C., Lien, G. and Hardaker, J. B. (2014). Technical efficiency in competing panel data models: a study of Norwegian grain farming. *Journal of Productivity Analysis* 41: 321–337.

Kumbhakar, S. C., Parmeter, C. F. and Zelenyuk, V. (2020). Stochastic frontier analysis: foundations and advances. In: S. C. Ray, R. Chambers and S. C. Kumbhakar (eds), *Handbook of Production Economics*. New York, NY: Springer, Singapore.

Labajova, K., Hansson, H., Asmild, M., Göransson, L., Lagerkvist, C. J. and Neil, M. (2016). Multidirectional analysis of technical efficiency for pig production systems: the case of Sweden. *Livestock Science* 187: 168–180.

Lagerkvist, C. J., Hansson, H., Hess, S. and Hoffman, R. (2011). Provision of farm animal welfare: integrating productivity and non-use values. *Applied Economic Perspectives and Policy* 33(4): 484–509.

Lansink, A. O., Silva, E. and Stefanou, S. (2001). Inter-firm and intra-firm efficiency measures. *Journal of Productivity Analysis* 15(3): 185–199.

Lansink, A. O., Kyösti, P. and Bäckman, S. (2002). Efficiency and productivity of conventional and organic farms in Finland 1994–1997. *European Review of Agricultural Economics* 29(1): 51–65.

Lastra-Bravo, X. B., Hubbard, C., Garrod, G. and Tolón-Becerra, A. (2015). What drives farmers' participation in EU agri-environmental schemes? Results from a qualitative meta-analysis. *Environmental Science & Policy* 54: 1–9.

Latruffe, L., Bravo-Ureta, B. E., Carpentier, A., Desjeux, Y. and Moreira, V. H. (2017). Subsidies and technical efficiency in agriculture: evidence from European dairy farms. *American Journal of Agricultural Economics* 99(3): 783–799.

Mack, G. and Huber, R. (2017). On-farm compliance costs and N surplus reduction of mixed dairy farms under grassland-based feeding systems. *Agricultural Systems* 154: 34–44.

Mack, G., Ritzel, C. and Jan, P. (2020). Determinants for the implementation of action-, result- and multi-actor-oriented agri-environment schemes in Switzerland. *Ecological Economics* (accepted).

Mamardashvili, P., Bokusheva, R. and Schmid, D. (2014). Heterogeneous farm output and technical efficiency estimates. *German Journal of Agricultural Economics* 63(1): 16–30.

Mann, S. (2008). Doing it the Swiss way. *EuroChoices* 2(3): 32–35.

Minviel, J. J. and Latruffe, L. (2017). Effect of public subsidies on farm technical efficiency: a meta-analysis of empirical results. *Applied Economics* 49(2): 213–226.

O'Donnell, C. J., Rao, D. P. and Battese, G. E. (2008). Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. *Empirical Economics* 34(2): 231–255.

Orea, L. and Kumbhakar, S. C. (2004). Efficiency measurement using a latent class stochastic frontier model. *Empirical Economics* 29(1): 169–183.

Orea, L., Pérez, J. A. and Roibás, D. (2015). Evaluating the double effect of land fragmentation on technology choice and dairy farm productivity: a latent class model approach. *Land Use Policy* 45: 189–198.

Pavlis, E. S., Terkenli, T. S., Kristensen, S. B. P., Busck, A. G. and Cosor, G. L. (2016). Patterns of agri-environmental scheme participation in Europe: indicative trends from selected case studies. *Land Use Policy* 57: 800–812.

Pitt, M. M. and Lee, L.-F. (1981). The measurement and sources of technical inefficiency in the Indonesian weaving industry. *Journal of Development Economics* 9(1): 43–64.

Rasmussen, S. (2010). Scale efficiency in Danish agriculture: an input distance–function approach. *European Review of Agricultural Economics* 37(3): 335–367.

Renner, S., Glauben, T. and Hockmann, H. (2014). Measurement and decomposition of flexibility of multi-output firms. *European Review of Agricultural Economics* 41(5): 745–773.

Sauer, J. and Morrison Paul, C. J. (2013). The empirical identification of heterogeneous technologies and technical change. *Applied Economics* 45(11): 1461–1479.

Schmidt, P. and Sickles, R. C. (1984). Production frontiers and panel data. *Journal of Business and Economic Statistics* 2(4): 367–374.

Tzouvelekas, V., Pantzios, C. J. and Fotopoulos, C. (2001). Technical efficiency of alternative farming systems: the case of Greek organic and conventional olive-growing farms. *Food Policy* 26(6): 549–569.

Vigani, M. and Dwyer, J. (2020). Profitability and efficiency of high nature value marginal farming in England. Journal of Agricultural Economics 71(2), 439–464.

Zhu, X. and Lansink, A. O. (2010). Impact of CAP subsidies on technical efficiency of crop farms in Germany, the Netherlands and Sweden. *Journal of Agricultural Economics* 61(3): 545–564.

Zhu, X. and Milán Demeter, R. (2012). Technical efficiency and productivity differentials of dairy farms in three EU countries: the role of CAP subsidies. *Agricultural Economics Review* 13(1): 66–92.

Appendix

Estimated parameters of the LCSFM (transformed by geometric means of the entire sample)[1]

	Class 1 "most productive"		Class 2 "average productive"		Class 3 "least productive"	
	Coefficient	Std.Error	Coefficient	Std.Error	Coefficient	Std.Error
Constant	0.257	0.046	0.088	0.009	−0.070	0.009
ln(x1) (Land)	0.205	0.012	0.220	0.011	0.202	0.014
ln(x2) (Labour)	0.087	0.012	0.100	0.009	0.111	0.014
ln(x3) (Capital)	0.227	0.013	0.218	0.013	0.225	0.016
ln(x4) (Materials)	0.511	0.014	0.538	0.013	0.593	0.016
t (Time trend)	0.001	0.001	−0.003	0.001	−0.006	0.002
ln(x1)*ln(x1)	0.039	0.034	−0.171	0.034	−0.096	0.045
ln(x1)*ln(x2)	−0.091	0.027	0.043	0.025	0.082	0.036
ln(x1)*ln(x3)	0.076	0.032	0.145	0.025	0.060	0.035
ln(x1)*ln(x4)	−0.196	0.026	−0.196	0.026	−0.152	0.040
ln(x1)*t	0.009	0.003	0.005	0.003	−0.011	0.004
ln(x2)*ln(x2)	0.088	0.032	−0.028	0.040	−0.081	0.043
ln(x2)*ln(x3)	−0.052	0.032	−0.022	0.025	0.059	0.040
ln(x2)*ln(x4)	0.088	0.029	0.032	0.025	−0.025	0.039
ln(x2)*t	−0.004	0.003	−0.006	0.003	−0.001	0.004
ln(x3)*ln(x3)	0.004	0.037	−0.124	0.021	−0.241	0.059
ln(x3)*ln(x4)	0.060	0.030	0.039	0.024	0.072	0.049
ln(x3)*t	−0.011	0.003	−0.008	0.003	0.013	0.004
ln(x4)*ln(x4)	0.085	0.034	0.276	0.024	0.177	0.050
ln(x4)*t	0.013	0.002	0.008	0.003	0.000	0.004
t*t	0.000	0.000	−0.001	0.000	−0.001	0.000
Sigma $= \sqrt{\sigma_u^2/\sigma_v^2}$	0.127	0.011	0.140	0.005	0.270	0.005
Lambda $= \sigma_u/\sigma_v$	0.272	0.496	1.171	0.144	3.541	0.241

[1]Note that the first order coefficients of the LCSFM are calculated at the geometric mean of the entire sample and therefore differ from the elasticities of the three classes presented in Table 3 because the latter are evaluated at their corresponding sample means, not at the mean of the entire sample.