Latent Class Modelling for a Robust Assessment of Productivity: Application to French Grazing Livestock Farms

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Abstract

Our objective is to extend the latent class stochastic frontier (LCSFM) model to compute productivity change, using the robust transitive productivity Färe-Primont index. The application is to three types of grazing livestock farms in France over the period 2002–2016. The LCSFM identified two classes of farms, intensive farms and extensive farms. Results indicate that productivity change and its components show only small differences between the LCSFM and the pooled model that does not account for heterogeneity. Differences across classes exist, but depend on farm type.

Keywords: *Efficiency*; *Färe-Primont*; *France*; *grazing livestock farms*; *latent class stochastic frontier*; *productivity*.

JEL classifications: *C01, D24, Q12*.

1. Introduction

Over the last decades, understanding agricultural total factor productivity (TFP) has been a cornerstone topic in the economic literature (Coelli and Rao, 2005) but also a

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prominent support in the design of many agricultural policies. For instance, if TFP is scaled down by technical regress, a policy that encourages the adoption of new technologies (through investment subsidies, for example) might limit this effect. By contrast, if TFP is affected by major efficiency decrease, policies implementing farmer's training programs may alleviate this effect. In agriculture TFP is a crucial indicator for the development of the sector but it is also a necessary condition to meet the challenges of the growing world population and the changes in nutritional habits (Alexandratos and Bruinsma, 2012; Fuglie, 2015). Paradoxically, TFP increase may raise the question of agricultural sustainability due to the negative environmental impacts of agriculture in the form of, for example, greenhouse gases (GHG) emissions, soil degradation, water pollution, biodiversity loss (Valin *et al*., 2013; Benton and Bailey, 2019).

Although the relation between agriculture and environment is complex, it has often been simplified through the dual lenses of input intensification and land extensification. As underlined by Coomes *et al*. (2019, p. 22): 'debates over the future of farming systems and agriculture continue to focus heavily on the socio-ecological trade-offs along extensification or intensification pathways for growth'. Specifically, intensification refers to the increase of non-land inputs like fertilisers and pesticides (Villoria, 2019), which results in the generation of environmental externalities. It is not clear-cut in the literature that extensive farming is more environmentally friendly (Phalan *et al*., 2016; Balmford *et al*., 2018), although there is evidence that agricultural intensification has negative local and global consequences (Tilman *et al*., 2002). For instance, Reidsma *et al*. (2006) and Kleijn *et al*. (2009) found a negative relation between intensively used areas and biodiversity. The performance of both systems is also debated and more case studies are needed to increase knowledge. Such knowledge is useful to help design agri-environmental schemes in the European Union's Common Agricultural Policy (CAP), which aim at compensating the loss in economic performance when environmentally friendly practices are used.

Our aim is to contribute to understanding productivity performance of the two systems. In addition, our study contributes to the methodological developments evaluating productivity of heterogeneous technologies, by using latent class stochastic frontier modelling (LCSFM) to calculate TFP for production technologies based on the intensive versus extensive characteristics of the farms under assessment. Albeit the classification of farms into the intensive/extensive categories is a simple calculus that can be done a priori (Temme and Verburg, 2010),[1] Alvarez *et al*. (2012) argued that LCSFM is a 'superior method' for distinguishing heterogeneous technologies. Orea and Kumbhakar's (2004) LCSFM is a single-stage approach to estimate efficiency and TFP while accounting for technological heterogeneity, that combines the stochastic frontier framework and the latent structure of the data. Here we provide a methodological contribution by extending the LCSFM to estimate productivity and its components with robust indices. While a few studies have examined TFP change of intensive and extensive farming systems using LCSFM (Alvarez and del Corral, 2010; Kellermann and Salhofer, 2014), none of those studies have used the new class of 'proper' productivity indices (which includes the Färe-Primont, the Geometric Young and

[1]See also EUROSTAT glossary for a definition of intensive and extensive farming (https://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:Extensive_farming)

the Lowe indices[2]) that satisfy more axioms (O'Donnell, 2018). Among those axioms, the transitivity property allows for multi-lateral and multi-temporal comparisons. As shown by O'Donnell (2011), chained indices, as proposed for example by Kellermann and Salhofer (2014), fail to satisfy the identity property. We extend the Färe-Primont productivity index to the LCSFM. While previous studies only focused on dairy production, our application is to beef cattle farms, dairy farms and mixed fieldcrop-grazing livestock farms in France during 2002–2016.

The rest of the article is structured as follows. The second section presents the methodological framework, and the third section presents the data. The fourth section explains the results and the fifth section concludes.

2. Methodology

2.1. The LCSFM framework

We start with the (classic) stochastic frontier analysis, which is a composed error model for the ith farm in the tth period. First, let us describe the production technology as follows:

$$T = \left\{ \left(x, y\right) \in \mathbb{R}^{K+L} \right) | x \text{ can produce } y \right\} \tag{1}$$

where $x \in \mathbb{R}^K$ and $y \in \mathbb{R}^L$ denote the vectors of inputs and outputs, respectively.

T can also be represented using an output distance function $D_o(x, y)$. It is common in agricultural productivity studies to use second-order flexible functional forms to describe the production function, such as the translog. However, the unrestricted version of this functional form fails to satisfy curvature properties along with axioms associated with the measure of proper productivity indices (O'Donnell, 2014, 2016). To this end, restrictive translog functional forms can be considered (Njuki *et al.*, 2018a). In our case, following the linear homogeneity property of the output distance function, we have used the following functional form:

$$\ln y_{1it} = \tau + \sum_{j=1}^{T} \alpha_j D_{jit} t + \sum_{k=1}^{K} \beta_k \ln x_{kit} + \eta z_{it} - \delta \ln \frac{y_2}{y_1} + v_{it} - u_{it} \tag{2}$$

where $i = 1, \cdots, N; (t, j) = 1, \cdots, T$; D_j are time dummies during the period 2002–2016, and thereby allow the rate of technical change to vary from year to year[3]; z_{it} is a contextual variable capturing the firm's operating conditions. As formulated, equation (2) is an output distance function with two outputs (y_1, y_2); $\Omega = (\tau, \alpha, \beta, \eta, \delta, \sigma_u, \sigma_v)$ is the vector of production function parameters; $\sum_{k=1}^{K} \beta_k = r$ is the scale elasticity; $\varepsilon_{it} = v_{it} - u_{it}$; v_{it} is the random fluctuation term, assumed to follow a normal distribution, and u_{it} represents the technical inefficiency term that is assumed to follow a half-normal distribution. v_{it} and u_{it} are independently distributed from each other and from the regressors. σ_u^2 is the variance of the one-sided error term u_{it} and σ_v^2 is the variance of the two-sided error term v_{it}.

Technological heterogeneity implies that the sample can be split into C different latent classes, each class c having the following production function:

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[2]The last two indices require prices and value shares information.

[3]In some studies the rate of technical change is assumed to change each five years (Njuki *et al.*, 2018b). We have relaxed this assumption in our case.

$$\ln y_{1it} = \tau_c + \sum_{j=1}^{T} \alpha_{jc} D_{jit} t + \sum_{k=1}^{K} \beta_{kc} \ln x_{kit} + \eta_c z_{it} - \delta_c \ln \frac{y_{2it}}{y_{1it}} + v_{it|c} - u_{it|c} \tag{3}$$

The prior probability $\Pi(i,t,c)$ of observation i in period t belonging to class c is parameterised using the following multinomial logit function:

$$\Pi(i,t,c) = \frac{\exp(q_{it}, t; \gamma_c)}{\sum_{j=1}^{J} \exp(q_{it}, t; \gamma_c)}; c = 1, \cdots, C; \gamma_C = 0; 0 \le \Pi(i,t,c) \le 1; \sum_c \Pi(i,t,c) = 1 \tag{4}$$

where q_{it} is the vector of separating variables explaining the probability of belonging to a specific class.

In equation (4) the separating variables are period- and firm-specific variables. Contrary to other studies who assumed a priori that a firm or farm belongs permanently to a specific class (e.g. Greene, 2005; Alvarez and del Corral, 2010; Cillero *et al.*, 2019), here we model the prior probabilities as time dependent instead of fixed through time. Only Orea *et al.* (2015) modelled a change over time, through a pooled-LCSFM where the prior probabilities change over time, while we explicitly consider time trend as part of the separating variables.

The unconditional probability of observing farm i in period t is obtained as:

$$P(i,t) = \sum_{c=1}^{C} \Pi(i,t,c) \times P(i,t|c) \tag{5}$$

where $P(i,t|c)$ is the probability of farm i belonging to class c in period t:

$$P(i,t|c) = LF_{it}(\Omega_c) = \frac{2}{\sqrt{\sigma^2_{v|c} + \sigma^2_{uit|c}}} \phi\left(\frac{\varepsilon_{it|c}}{\sqrt{\sigma^2_{v|c} + \sigma^2_{uit|c}}}\right) \Phi\left(-\left(\sigma_{uit|c}/\sigma_{v|c}\right) \frac{\varepsilon_{it|c}}{\sqrt{\sigma^2_{v|c} + \sigma^2_{uit|c}}}\right) \tag{6}$$

where $\Omega_c = (\gamma_c, \tau_c, \alpha_c, \beta_c, \eta_c, \delta_c, \sigma_{u|c}, \sigma_{v|c})$ are the parameters of the likelihood (LF_{it}) to be estimated for each class c. To prevent biased coefficients and efficiency scores, the inefficiency term u_{it} is considered to be heteroscedastic.

The log-likelihood of the LCSFM (log LF) can then be written as:

$$\log LF = \sum_{i=1}^{N} \sum_{t=1}^{T} \log\left(\sum_{c=1}^{C} \Pi(i,t,c) \times P(i,t|c)\right) \tag{7}$$

Each farm i can be assigned to a specific class by considering the largest posterior probability of belonging to class c in period t, computed as:

$$P(c|i,t) = \frac{\Pi(i,t,c) \times P(i,t|c)}{\sum_{c=1}^{C} \Pi(i,t,c) \times P(i,t|c)} \tag{8}$$

As underlined in Parmeter (2014), some observations may have a probability of belonging to a specific class close to unity and, therefore, it is consistent to use the technological parameters of this class for these observations. Moreover, this choice is also guided by the value of the average posterior probability, which, in most empirical cases, is very high (Orea *et al.*, 2015). In this case, using the parameters of the most probable class or the average probability yields very similar results as using a weighted average of class-specific parameters.

To select the number of classes, we compare the Akaike Information Criterion (AIC) across models, as suggested by Orea and Kumbhakar (2004).

For each class c in period t, the inefficiency of each farm i in the class can be estimated using the formula of Jondrow *et al.* (1982):

$$E\left[u_{it|c}|\varepsilon_{it|c}\right]=\mu_{*it|c}+\sigma_{*it|c}\left[\frac{\phi\left(-\mu_{*it|c}/\sigma_{*it|c}\right)}{1-\Phi\left(-\mu_{*it|c}/\sigma_{*it|c}\right)}\right] \tag{9}$$

where $\mu_{*it|c}=-\frac{\varepsilon_{it|c}\sigma^2_{uit|c}}{\sigma^2_{uit|c}+\sigma^2_{v|c}}$ and $\sigma_{*it|c}=\frac{\sigma^2_{uit|c}\sigma^2_{v|c}}{\sigma^2_{uit|c}+\sigma^2_{v|c}}$; the efficiency being computed as $\exp\left(-E\left[u_{it|c}|\varepsilon_{it|c}\right]\right)$.

2.2. *Computation of a robust productivity index*

We now extend the LCSFM to the estimation of productivity with the Färe-Primont productivity index. The latter index, as recommended by O'Donnell (2016) and Njuki *et al.* (2018b), is a robust TFP index in the sense that it is multiplicatively complete. This means that it can be written as the ratio of an aggregated output to an aggregated input, and it satisfies the transitivity assumption necessary for multi-lateral and multi-temporal comparisons.

Formally, for each farm i in period t, a multiplicatively complete TFP index can be written as:

$$TFP_{it}=\frac{Q(y_{it})}{X(x_{it})} \tag{10}$$

where $Q()$ and $X()$ are aggregator functions which must be non-negative, non-decreasing and linearly homogeneous.[4] Examples of functions satisfying these properties are output and input distance functions such as $Q(y)=D^{\bar{t}}_O(\bar{x},y,\bar{z})$ and $X(x)=D^{\bar{t}}_I(x,\bar{y},\bar{z})$, where $\bar{x},\bar{y},\bar{z}$ are, respectively, fixed vectors of inputs, outputs and contextual variables, and $\bar{t}$ is a fixed reference period. The fixed vectors ensure the transitivity property.

We then have:

$$TFP_{hs,it}=\frac{D^{\bar{t}}_O(\bar{x},y_{it},\bar{z})}{D^{\bar{s}}_O(\bar{x},y_{hs},\bar{z})}\frac{D^{\bar{s}}_I(x_{hs},\bar{y},\bar{z})}{D^{\bar{t}}_I(x_{it},\bar{y},\bar{z})} \tag{11}$$

Productivity indices like (11) include the Lowe, Geometric Young and Färe-Primont indices. While equation (10) is a measure of the TFP level of farm i in period t, equation (11) reflects the TFP changes between farm i in period t, and farm h in period s.

When the technology exhibits Hick-neutrality and homotheticity, and is homogeneous of degree r, then:

$$D^t_O(x,y,z)=\frac{Q(y)}{A^t(z)X(x)^r} \tag{12}$$

where $Q(y)=D^{\bar{t}}_O(\bar{x},y,\bar{z})$, $X(x)=D^{\bar{s}}_I(x,\bar{y},\bar{z})$ and $A^t(z)=D^{\bar{t}}_O(\bar{x},\bar{y},\bar{z})^2/D^t_O(\bar{x},\bar{y},z)$ (see proposition 10 in O'Donnell, 2016).

[4]Several other properties must also be satisfied like weak monotonicity, transitivity, circularity and so on.

Hence, TFP is:

$$TFP(x,y) = A^t(z)X(x)^{r-1}D_O^t(x,y,z) \tag{13}$$

In the case where the farms are technically efficient and constant returns to scale are assumed, then the last two terms of equation (13) equal unity each.

TFP change can be written as follows:

$$TFP_{hs,it} = \frac{A^t(z_{it})}{A^s(z_{hs})}\frac{X(x_{it})^{r-1}}{X(x_{hs})^{r-1}}\frac{D_O^t(x_{it},y_{it},z_{it})}{D_O^s(x_{hs},y_{hs},z_{hs})} \tag{14}$$

The first component in equation (14) relates to technical change but also changes in the operating conditions. The last two components are the scale and the efficiency changes respectively.

As pointed out in O'Donnell (2014), it is common to assume a translog functional form for $D_O^t(x,y,z)$. However, the translog violates properties (strong disposability of inputs and outputs, homogeneity of degree r, homotheticity and Hicks-neutrality) which are required to construct a proper productivity index. If the Cobb-Douglas form is retained, then:

$$TFP_{hs,it} = \prod_{l=1}^{L}\left(\frac{y_{l,it}}{y_{l,hs}}\right)^{\delta_h}\prod_{k=1}^{K}\left(\frac{x_{k,hs}}{x_{k,it}}\right)^{\lambda_k} \tag{15}$$

with $\sum_{l=1}^{L}\delta_l = 1$ and $\sum_{k=1}^{K}\lambda_k = 1$. Specifically, $\lambda_k = \beta_k / r$.[5] Moreover, δ_l is approximated using the output distance function.

To compute the Färe-Primont TFP index, we write the output levels from equation (3):

$$y_{1it}^{1-\delta_c}y_{2it}^{\delta_c} = \exp(\tau_c)\bullet\exp\left(\sum_{j=1}^{T}\alpha_{jc}D_{jit}t\right)\bullet\prod_{k=1}^{K}x_{kit}^{\beta_{kc}}\bullet\exp(\eta_c z_{it})\bullet\exp\left(v_{it|c}\right)\bullet\exp\left(-u_{it|c}\right) \tag{16}$$

Hence, the Färe-Primont TFP index for farms h and i (in periods s and t) belonging to class c can be written as follows:

$$\begin{aligned} TFP_{hs,it|c} = {} & \left[\frac{\exp\left(\sum_{j=1}^{T}\alpha_{jc}D_{jit}t\right)}{\exp\left(\sum_{j=1}^{T}\alpha_{jc}D_{jis}s\right)}\right]\bullet\left[\exp\left(u_{ms|c}-u_{it|c}\right)\right] \\ & \left[\prod_{k=1}^{K}\frac{x_{kit}^{\beta_{kc}-\lambda_{kc}}}{x_{kms}^{\beta_{kc}-\lambda_{kc}}}\right]\bullet\left[\frac{\exp(\eta_c z_{it})}{\exp(\eta_c L z_{ht})}\right]\bullet\left[\exp\left(v_{it|c}-v_{ms|c}\right)\right] \end{aligned} \tag{17}$$

where $\lambda_{kc} = \beta_{kc}/r_c$ and $r_c = \sum_{k=1}^{K}\beta_{kc}$ is the scale elasticity.

Equation (17) decomposes TFP into five components which are the five terms in the right-hand side of the equation. The first term is technical change component; the second term is (output) technical efficiency change; the third term is (output) scale change; the fourth term is the change in contextual variables, called here contextual change, that is to say, changes in the farm's operating conditions; the last term is the statistical noise index which accounts for the residual component. In our empirical application, the operating conditions are proxied by one single contextual variable

[5]These properties ensure that the aggregator functions are linearly homogeneous.

which is fixed over time (a dummy for farm location), implying that the fourth component equals unity when the same farm is compared over time.

3. Data

Our study covers three types of French grazing farms: farms specialised in beef cattle; farms specialised in dairy; and mixed farms, producing fieldcrops and breeding grazing livestock. We consider these different farm types separately, thus technological heterogeneity is assessed within each farm type respectively. The data used are annual farm-level bookkeeping and structural data from the French Farm Accountancy Data Network (FADN) during the period 2002 to 2016.

In line with the existing literature (Asmild *et al*., 2014; Latruffe *et al*., 2017; Cillero *et al*., 2018; Dakpo *et al*., 2018a, 2018b; Wimmer and Sauer, 2020), the production specification accounts for two outputs (main and secondary products) and four or five inputs. For dairy farms, the main output (y_1) is the quantity of milk produced (in tons) and the secondary output (y_2) is the aggregation of all other outputs (expressed in 2015 constant euros[6]). For beef farms, the main output (y_1) is the meat production (in 2015 euros) and all other outputs are grouped into the secondary output (y_2) (in 2015 euros). In the case of mixed farms, y_1 is the total crop production (in 2015 euros), while y_2 is the total animal production (in 2015 euros).[7] Five inputs (x_1, x_2, x_3, x_4, x_5) are employed in the production function, namely: utilised agricultural area (UAA) (in hectares – ha); total labour (in full time equivalent annual working units – AWU); herd size (in livestock units[8]); intermediate consumption (in 2015 thousand euros)[9]; and fixed assets (in 2015 thousand euros). An exception is for the beef cattle farms where four inputs are used instead. Due to the high correlation between UAA and herd size, herd size is not used as a specific input, instead herd is included within fixed assets to reduce collinearity issues, as in Reinhard *et al*. (1999). In addition to the inputs, a contextual variable (z) is included in the production function for all three farm types, which is a dummy variable indicating whether the farm is located in a less favoured area (LFA) or not.[10]

To capture production heterogeneity, we consider four main criteria: (i) farm intensity, which is proxied here by three variables: the grazing pressure in terms

[6]We used the price indices provided by the French Statistical Agency – INSEE (https://www.insee.fr/en/metadonnees/source/indicateur/p1652/description; https://www.insee.fr/en/metadonnees/source/indicateur/p1657/description).

[7]It is worth pointing out that, although most outputs used here are measured in real terms, the changes in the price of the outputs could be different to the deflator index. In this case, changes in prices could be misled with productivity changes. This is a general data limitation in productivity analyses.

[8]'The livestock unit [...] is a reference unit which facilitates the aggregation of livestock from various species and age as per convention, via the use of specific coefficients established initially on the basis of the nutritional or feed requirement of each type of animal [...].' (http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:Livestock_unit_(LSU)).

[9]The intermediate consumption includes all the costs related to animal food consumption, veterinary expenses, fertilisers and pesticides use, seeds purchase and other variable materials.

[10]The LFAs are defined in the European Union's Rural Development Policy, and are areas with natural handicaps.

of stocking rate (calculated as the number of livestock units per ha of UAA) (q_1); the share of permanent grassland in UAA (q_2); and capital intensity measured by the ratio of fixed assets per labour unit (q_3); (ii) environmental practices, proxied by the amount of CAP agri-environmental subsidies per hectare of UAA (q_4); (iii) weather conditions, included through average daily effective rainfall[11] (in mm) and temperature (in degrees Celsius) (q_5, q_6); (iv) and external factors, namely the dummy for farm location in LFA, and the time trend. The selection of some of these separating variables to capture production heterogeneity (stocking rate, capital intensity, environmental practices, LFA) is based on the existing literature of latent class modelling in farming (Sauer and Paul, 2013; Alvarez and Arias, 2015; Cillero *et al.*, 2019). We include the share of permanent grassland following Kellermann and Salhofer (2014) who considered an a priori (non-latent) classification where farms are split into two groups, one consisting of farms that rely on permanent grassland and the other group made up of fodder-crop farms. Regarding weather characteristics, in a recent paper Perez-Mendez *et al.* (2019) stressed the indirect role played by weather variables on land and animal productivity. The authors included the weather variables in the production function, but this is not possible with our specification since these authors have used a translog production function (with nested sub-functions). For this reason we included the weather characteristics in the separating variables.

Finally, we model heteroscedasticity through the inclusion of determinants of inefficiency, whose selection is based on existing literature on farm efficiency and productivity (Samarajeewa *et al.*, 2012; Tiedemann and Latacz-Lohmann, 2013; Latruffe *et al.*, 2017; Paul and Shankar, 2018; Zhang *et al.*, 2019). The determinants that we use are: the farmer's age (E_1); the total CAP operational subsidies per hectare of UAA (E_2); the share of hired labour in total labour (E_3); the share of rented UAA in total UAA (E_4); and a dummy variable taking the value one if the farmer has none or primary education, and the value zero if the farmer has secondary education or above (E_5).

Table 1 shows some descriptive statistics of the variables used, per type of farm. The average UAA over the period is 120 ha, 91 ha and 157 ha for beef cattle, dairy and mixed farms, respectively. The herd size is, respectively, 137, 100 and 115 livestock units for beef, dairy and mixed farms. This results in a higher stocking rate for beef cattle and dairy farms on average. The lower stocking rate for mixed farms can be explained by the fact that crop production represents, on average, 55% of the total UAA for this farm type, while the figure is 13% and 21% for beef cattle and dairy farms, respectively. Moreover, more than 83% of beef cattle farms are located in LFA, compared to 50% and 36% for dairy and mixed farms respectively. Beef farms have the highest share of permanent grassland, and receive the largest amount of agri-environmental subsidies per hectare of UAA, on average. Finally, mixed farms exhibit the highest capital to labour ratio. The high coefficients of variation for most variables (>0.25) reveal the presence of within-sample heterogeneity and support the relevance of a latent class model.

[11]Effective rainfall accounts for gross rainfall and evapotranspiration.

Table 1
Descriptive statistics of the French FADN farms during 2002–2016

Variables	Beef cattle farms		Dairy farms		Mixed farms	
	Mean	CV	Mean	CV	Mean	CV
Output distance function						
Main production (for dairy farms – tons of milk; for beef cattle farms – thousand euros) or crop production (for mixed farms – thousand euros):y_1	85.5	0.67	345.5	0.61	92.4	0.82
Other output (for dairy and beef cattle farms) or animal production (for mixed farms) (thousand euros):y_2	25.6	1.70	67.0	0.85	163.7	0.75
UAA (ha):x_1	120	0.56	91	0.57	157	0.62
Total labour (AWU):x_2	1.5	0.47	1.9	0.50	2.2	0.54
Herd size (livestock units):x_3	137	0.59	100	0.57	115	0.64
Intermediate consumption (thousand euros):x_4	62.2	0.66	98.5	0.67	140.5	0.66
Fixed assets (thousand euros)[a]:x_5	269.9	0.62	192.2	0.87	243.9	0.81
Dummy equal to one when farm located in LFA:LFA	0.83	0.44	0.50	1.00	0.36	1.34
Separating variables						
Stocking rate (livestock units per ha of UAA):q_1	1.2	0.35	1.2	0.36	0.8	0.45
Share of permanent grassland in UAA (%):q_2	51	0.63	40	0.81	24	0.74

Table 1
(*Continued*)

Variables	Beef cattle farms		Dairy farms		Mixed farms	
	Mean	CV	Mean	CV	Mean	CV
Capital to labour ratio (thousand euros per AWU):q_3	88.7	0.70	102.7	0.74	112.4	0.66
Agri-environmental subsidies per hectare of UAA (euros): q_4	37.0	1.19	23.2	1.81	9.5	2.73
Average daily effective rainfall (mm):q_5	0.9	0.59	1.1	0.61	0.8	0.52
Average daily temperature (degrees Celsius):q_6	10.9	0.13	10.5	0.15	11.1	0.10
Inefficiency determinants						
Farmer's age (years):E_1	47.2	0.18	47.1	0.18	47.2	0.19
Operational subsidies per ha of UAA (euros per ha):E_2	469.3	0.30	384.8	0.34	402.5	0.26
Share of hired labour in total labour (%):E_3	6	2.29	7	2.15	12	1.52
Share of rented area in total UAA (%):E_4	71	0.44	80	0.36	87	0.26
Dummy equal to one if no education or primary education:E_5	0.23	1.85	0.24	1.77	0.27	1.64

***Notes:*:** CV stands for coefficient of variation. [a] For beef farms, fixed assets include herd and the figures for herd size are shown for information only (herd size has not been included as a specific input in the output distance function).

4. Results

For each farm type, we ran the estimation on a LCSFM with four classes, then a LCSFM with three classes, and finally a LCSFM with two classes.[12] Then the AIC values and convergence criteria of these three LCSFMs were compared in order to select the appropriate number of classes. For the three farm types we retained two classes. For comparison purpose, we also estimated the model with one single class, that is, for the whole (farm-type) sample pooled.

The estimated coefficients of this pooled model (a) and of the LCSFM with two classes (b) are presented in Tables 2 to 4 for each farm type. The average posterior probabilities using observations belonging to each class are very high (more than 83% for beef cattle farms, 87% for dairy farms and 69% for mixed farms).

For beef cattle farms, the probability of belonging to class 1 is positively related to stocking rate while agri-environmental subsidies per hectare of UAA have a negative impact. Based on these results, we deem class 1 as the more intensive. The conclusion is very similar for dairy farms for which the probability of being in class 1 is positively explained by stocking rate and capital to labour ratio, but negatively related to the share of permanent grassland and agri-environmental subsidies per hectare of UAA. Thus, similarly to beef cattle farms, class 1 is the more intensive class. In the case of mixed farms, however, belonging to class 1 is positively related to the share of permanent grassland, the amount of agri-environmental subsidies per hectare of UAA and the location in LFA, but negatively related to capital to labour ratio. Here class 1 can be deemed the more extensive. In the following, we will label 'intensive class', class 1 for beef cattle and dairy farms and class 2 for mixed farms, while we will label 'extensive class', class 2 for beef cattle and dairy farms and class 1 for mixed farms.

For dairy and mixed farms, being located in LFA decreases the probability to be in the intensive class, while the opposite is true for beef cattle farms. This counter-intuitive finding may be explained by the fact that, as previously mentioned, more than 83% of beef cattle farms are located in these disadvantage areas. Regarding weather variables, higher temperature increases (while higher rainfall decreases) the probability of being in the intensive class in the case of beef cattle and dairy farmers. In the case of mixed farms the impact of weather variables are opposite compared to the beef cattle and dairy farmers. These significant results clearly show the importance of considering weather variables when modelling farm production technologies. The trend has a negative influence on the probability of being in the intensive class for all types of farms, suggesting that more and more farms belong to the extensive class over time.

Regarding the separate production technologies, the strong disposability assumption (shown by the coefficients for the inputs and the output, which are also elasticities) is satisfied, except for the elasticity of herd size that is significantly negative for the extensive class of mixed farms. This result may be related to the trade-offs between the two main activities (crop vs. animal productions) on mixed farms, and to the extensification strategy of farms in this class. In terms of scale effects, beef cattle and mixed farms exhibit increasing returns to scale, while the scale elasticity is very close to unity for dairy farms, implying constant returns to scale.

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[12]The maximum likelihood estimations were obtained using the maxLik package (Henningsen and Toomet, 2011) in the R software (R Core Team, 2018).

Table 2
Estimated coefficients of the latent Cobb-Douglas production frontier: comparison of the pooled model (a) and the LCSFM (b) for beef cattle farms

		LCSFM with two classes (b)	
Variables	Pooled model (a)	Class 1 (intensive)	Class 2 (extensive)
Production function			
Intercept	0.282***	0.316***	–0.112*
log(x_1: UAA)	0.145***	0.292***	0.262***
log(x_2: total labour)	0.089***	0.058***	0.105***
log(x_4: intermediate consumption)	0.631***	0.523***	0.576***
log(x_5: fixed assets including herd)	0.181***	0.146***	0.166***
log(y_2/y_1)	–0.09***	–0.044***	–0.137***
Dummy *LFA*	–0.104***	–0.232***	–0.208***
Trend × Dummy_{2003}	–0.039***	–0.028***	–0.043**
Trend × Dummy_{2004}	–0.018***	–0.013**	–0.009
Trend × Dummy_{2005}	–0.006	–0.004	0.01
Trend × Dummy_{2006}	–0.001	0.003	0.005
Trend × Dummy_{2007}	–0.002	0.001	0.007
Trend × Dummy_{2008}	–0.001	0.001	0.007
Trend × Dummy_{2009}	–0.008***	–0.003	–0.005
Trend × Dummy_{2010}	–0.005***	0.001	0
Trend × Dummy_{2011}	–0.002	0.001	0.003
Trend × Dummy_{2012}	0.003**	0.006***	0.011***
Trend × Dummy_{2013}	0.003**	0.006***	0.01***
Trend × Dummy_{2014}	0.003**	0.006***	0.009***
Trend × Dummy_{2015}	0.001	0.005***	0.005**
Trend × Dummy_{2016}	–0.003***	0.002	0.001
Inefficiency determinants			
Intercept	–0.502***	0.958	–0.465***
Farmer's age:E_1	–0.014***	–0.073***	–0.01***
Operational subsidies per ha of UAA:E_2	–0.001***	–0.007***	–0.001***
Share of hired labour in total labour:E_3	–1.385***	–3.019	–1.237***
Share of rented area in total UAA:E_4	–0.543***	–0.038	–0.691***
Dummy no education or primary education:E_5	0.208***	0.284	0.249***
Noise component			
W_v	–3.504***	–3.327***	–5.514***
Separating variables			
Intercept	–	–8.625***	–
Stocking rate:q_1	–	4.873***	–
Share of permanent grassland in UAA:q_2	–	0.151	–
Capital to labour ratio:q_3	–	0.001	–
Agri-environmental subsidies per hectare of UAA: q_4	–	–0.003**	–
Average daily effective rainfall:q_5	–	–0.314***	–
Average daily temperature:q_6	–	0.12***	–
Dummy *LFA*	–	3.535***	–
Trend	–	–0.099***	–
Scale elasticity	1.05	1.02	1.11

Table 2
(*Continued*)

Variables	Pooled model (a)	LCSFM with two classes (b)	
		Class 1 (intensive)	Class 2 (extensive)
Average efficiency	0.78	0.95	0.73
Average posterior probability	1.00	0.85	0.83
Number of observations	8,401	4,814	3,587

Note:: *, **, *** indicate significance at the 10%, 5%, 1% level, respectively.

In terms of efficiency levels, the intensive class is on average more technically efficient than the extensive class for beef cattle and dairy farms, while in the case of mixed farms the two classes have similar average technical efficiency. The determinants of inefficiency vary not only between the different farm types but also across classes within a farm type. We describe here the results in terms of effect on efficiency, as it is classically done in the literature. Age positively influences technical efficiency for beef cattle farms and for the dairy farms' extensive class, while the impact on efficiency is negative for the pooled models and the intensive classes of dairy and mixed farms. For operational subsidies per hectare, the effect on technical efficiency is positive for beef cattle farms (pooled and classes) and for intensive dairy farms, while a negative impact is found in the case of dairy and mixed farms in the pooled model and for the extensive class. This is in line with the literature's ambiguous findings on the impact of subsidies on farms' technical efficiency, and confirms the role of context (Minviel and Latruffe, 2017). The share of hired labour has a positive effect on technical efficiency for the pooled and extensive beef cattle and mixed farms, while the effect is negative for the pooled dairy farms, and not significant for the other classes. The share of rented area has a positive effect on technical efficiency, except that it is not significant for the beef cattle intensive class, and for both dairy classes. Finally, the absence of education or primary education has a negative impact on technical efficiency for dairy farms, and for mixed pooled and extensive farms, while it is non-significant in the other cases.

The productivity (TFP) change and its components are presented in Table 5 for all farm types. Since all farm-type samples are unbalanced, the productivity change and its components are computed after balancing the samples each consecutive two years. Each farm is then compared to itself in the previous period if it is observed in this previous period. In Table 5, for each farm type, the last rows (b) show results of the LCSFM. On average in the LCSFM, the analysis of TFP shows a gloomy picture over the period 2002–2016 with a major decrease for dairy farms (–17%) while the decrease is moderate for mixed farms (–8%). In the case of beef cattle farms, there is almost no change (–1%) in TFP over the period. A closer look to the evolution of TFP (see Figure 1) shows a major drop for dairy and mixed farms in 2009 and 2016, revealing the negative consequences of the milk crises.

The major source of TFP decrease for dairy and mixed farms is technical regress (–11% and –9% respectively). As we modelled that the rate of technical change can change from year to year, other external forces like the changes in the institutional environment (e.g. CAP) may be at play here. In the case of dairy farms, the situation

Table 3
Estimated coefficients of the latent Cobb-Douglas production frontier: comparison of the pooled model (a) and the LCSFM (b) for dairy farms

Variables	Pooled model (a)	LCSFM with two classes (b) Class 1 (intensive)	Class 2 (extensive)
Production function			
Intercept	1.552***	1.518***	1.311***
log(x_1: UAA)	0.032***	0.142***	0.034***
log(x_2: total labour)	0.143***	0.165***	0.103***
log(x_3: herd size)	0.223***	0.148***	0.326***
log(x_4: intermediate consumption)	0.561***	0.502***	0.499***
log(x_5: fixed assets excluding herd)	0.05***	0.046***	0.049***
log(y_2/y_1)	–0.242***	–0.29***	–0.214***
Dummy *LFA*	–0.081***	–0.052***	0.041***
Trend × Dummy$_{2003}$	–0.021***	–0.015***	–0.035***
Trend × Dummy$_{2004}$	–0.008***	–0.009***	–0.016***
Trend × Dummy$_{2005}$	–0.008***	–0.013***	–0.014***
Trend × Dummy$_{2006}$	–0.01***	–0.016***	–0.012***
Trend × Dummy$_{2007}$	0.002	0	–0.003
Trend × Dummy$_{2008}$	0.01***	0.012***	0.006***
Trend × Dummy$_{2009}$	–0.012***	–0.013***	–0.014***
Trend × Dummy$_{2010}$	0.001	0	–0.001
Trend × Dummy$_{2011}$	0.009***	0.01***	0.005***
Trend × Dummy$_{2012}$	0.005***	0.008***	0.002
Trend × Dummy$_{2013}$	0.004***	0.007***	0.001
Trend × Dummy$_{2014}$	0.006***	0.009***	0.004***
Trend × Dummy$_{2015}$	–0.001**	0.001	–0.004***
Trend × Dummy$_{2016}$	–0.007***	–0.004***	–0.011***
Inefficiency determinants			
Intercept	–3.277***	–4.404***	–2.813***
Farmer's age:E_1	0.005***	0.029***	–0.004*
Operational subsidies per ha of UAA:E_2	0.001***	–0.007***	0.001***
Share of hired labour in total labour:E_3	0.175*	0.139	0.107
Share of rented area in total UAA:E_4	–0.129**	–0.253	–0.028
Dummy no education or primary education:E_5	0.372***	0.826***	0.38***
Noise component			
W_v	–4.36***	–4.074***	–4.786***
Separating variables			
Intercept	–	1.726***	–
Stocking rate:q_1	–	1.003***	–
Share of permanent grassland in UAA:q_2	–	–4.895***	–
Capital to labour ratio:q_3	–	0.007***	–
Agri-environmental subsidies per hectare of UAA: q_4	–	–0.01***	–
Average daily effective rainfall:q_5	–	–0.733***	–
Average daily temperature:q_6	–	0.072*	–

Table 3
(*Continued*)

Variables	Pooled model (a)	LCSFM with two classes (b) Class 1 (intensive)	Class 2 (extensive)
Dummy *LFA*	–	–1.355***	–
Trend	–	–0.072***	–
Scale elasticity	1.01	1.00	1.01
Average efficiency	0.83	0.95	0.81
Average posterior probability	1.00	0.88	0.87
Number of observations	15,060	8,238	6,822

Note: *, **, *** indicate significance at the 10%, 5%, 1% level, respectively.

is also worsened by a slight decrease in technical efficiency (–4%). Finally, although beef cattle farms have not registered a significant TFP change, they have nevertheless experienced positive change in the scale component (+13%). This change is, however, offset by a decrease in technical efficiency (–5%) and in the noise component (–10%). The evolution of the cumulative change of TFP components can be found in Figure 2. This figure reveals a clear pattern of technical efficiency decrease for beef cattle and dairy farms, while for mixed farms there is a slight improvement in technical efficiency. Only beef cattle farms exhibit improvement in the scale component. Another interesting feature is that the technical change component and TFP show the same patterns of evolution.

Coming now to specific classes with LCSFM, we observe that in the case of beef cattle farms, the extensive class records a much higher TFP growth than the intensive class. The reverse situation is observed in the case of dairy farms. In the mixed farms case, the results are very similar between the two classes. The decrease in TFP due to statistical noise (–10%) observed for the whole beef cattle farms sample is not visible when farms are separated into classes, with similar small positive changes for both classes. It is also interesting to note that, in all three farm type samples, although the intensive class farms are more technically efficient on average than extensive class farms, the former record no change in technical efficiency (score of unity). The extensive farms experience an increase in technical efficiency in the case of beef cattle farms (+10%) and mixed farms (+2%), but a decrease in the case of dairy farms (–5%).[13]

Comparing TFP results between the pooled model and the LCSFM shows that TFP changes are very similar in both models, with differences between models ranging from 0% to 3%. For dairy and mixed farms, the sources of TFP changes are also the same in the two models (pooled and LCSFM). By contrast, for beef cattle farms, the sources of TFP change are different. For example, for the whole sample, in the pooled model there is a 5% decrease in technical change along with a 2% increase in technical efficiency, and an additional 3% increase in the noise component. Contrarily, in the LCSFM technical change has increased (2%) while technical efficiency has decreased

[13]The evolution of TFP and its components of the different farm types per class can be found in the Appendix S1.

Table 4
Estimated coefficients of the latent Cobb-Douglas production frontier: comparison of the pooled model (a) and the LCSFM (b) for mixed farms

Variables	Pooled model (a)	LCSFM with two classes (b) Class 1 (extensive)	Class 2 (intensive)
Production function			
Intercept	0.187***	–0.021	0.486***
log(x_1: UAA)	0.068***	0.086***	0.048***
log(x_2: total labour)	0.139***	0.148***	0.124***
log(x_3: herd size)	0.02***	–0.03***	0.139***
log(x_4: intermediate consumption)	0.746***	0.778***	0.635***
log(x_5: fixed assets excluding herd)	0.093***	0.103***	0.069***
log(y_2/y_1)	–0.633***	–0.544***	–0.783***
Dummy *LFA*	–0.058***	–0.057***	–0.02*
Trend × Dummy$_{2003}$	–0.005	–0.022***	0.014*
Trend × Dummy$_{2004}$	0.002	–0.002	0.006
Trend × Dummy$_{2005}$	–0.006**	–0.005	–0.006
Trend × Dummy$_{2006}$	–0.001	0.003	–0.009***
Trend × Dummy$_{2007}$	0.023***	0.024***	0.019***
Trend × Dummy$_{2008}$	0.019***	0.015***	0.025***
Trend × Dummy$_{2009}$	–0.013***	–0.014***	–0.011***
Trend × Dummy$_{2010}$	0.012***	0.012***	0.009***
Trend × Dummy$_{2011}$	0.022***	0.023***	0.022***
Trend × Dummy$_{2012}$	0.021***	0.023***	0.017***
Trend × Dummy$_{2013}$	0.009***	0.005***	0.013***
Trend × Dummy$_{2014}$	0.006***	0.006***	0.008***
Trend × Dummy$_{2015}$	0.003***	0.004***	0.003
Trend × Dummy$_{2016}$	–0.006***	–0.006***	–0.007***
Inefficiency determinants			
Intercept	–3.597***	–5.401***	–4.672***
Farmer's age:E_1	0.009***	–0.003	0.036*
Operational subsidies per ha of UAA (euros/ha):E_2	0.001***	0.005***	0.0003
Share of hired labour in total labour:E_3	–0.334**	–1.752**	0.181
Share of rented area in total UAA:E_4	–0.941***	–1.383***	–2.351***
Dummy no education or primary education:E_5	–0.025	0.227	–0.375
Noise component			
W_v	–3.942***	–3.831***	–4.283***
Separating variables			
Intercept	–	–4.013***	–
Stocking rate:q_1	–	–0.159	–
Share of permanent grassland in UAA:q_2	–	3.357***	–
Capital to labour ratio:q_3	–	–0.003***	–
Agri-environmental subsidies per hectare of UAA: q_4	–	0.003*	–
Average daily effective rainfall:q_5	–	–0.475***	–
Average daily temperature:q_6	–	0.363***	–
Dummy *LFA*	–	0.763***	–
Trend	–	0.057***	–
Scale elasticity	1.07	1.09	1.02

Table 4
(*Continued*)

Variables	Pooled model (a)	LCSFM with two classes (b) Class 1 (extensive)	Class 2 (intensive)
Average efficiency	0.87	0.93	0.94
Average posterior probability	1.00	0.79	0.69
Number of observations	8,415	5,641	2,774

***Note:*:** *, **, *** indicate significance at the 10%, 5%, 1% level, respectively.

Table 5
Productivity (TFP) change and components between 2002 and 2016 in the LCSFM with several classes (b), and for the same classes using the pooled model results (a)

		TFP change	Technical change	Technical efficiency change	Scale change	Statistical noise index
Beef cattle farms						
Pooled model (a)[a]	Whole sample	0.99	0.95	1.02	1.01	1.03
	Class 1 (intensive)	1.04	0.95	1.03	1.01	1.06
	Class 2 (extensive)	1.12	0.95	1.10	1.00	1.07
LCSFM (b)	Whole sample	0.99	1.02	0.95	1.13	0.90
	Class 1 (intensive)	1.05	1.03	1.00	1.00	1.02
	Class 2 (extensive)	1.13	1.01	1.10	1.01	1.01
Dairy farms						
Pooled model (a)[a]	Whole sample	0.85	0.90	0.95	1.00	1.00
	Class 1 (intensive)	0.95	0.90	1.03	1.00	1.03
	Class 2 (extensive)	0.79	0.90	0.90	1.00	0.97
LCSFM (b)	Whole sample	0.83	0.89	0.96	1.01	0.97
	Class 1 (intensive)	0.92	0.94	1.00	1.00	0.98
	Class 2 (extensive)	0.81	0.85	0.95	1.00	1.00
Mixed farms						
Pooled model (a)[a]	Whole sample	0.94	0.91	1.01	1.01	1.01
	Class 1 (extensive)	0.95	0.91	1.02	1.01	1.02
	Class 2 (intensive)	0.95	0.91	1.01	1.01	1.02
LCSFM (b)	Whole sample	0.92	0.91	1.01	1.03	0.97
	Class 1 (extensive)	0.94	0.91	1.02	1.01	1.00
	Class 2 (intensive)	0.95	0.91	1.00	1.00	1.05

***Note:*:** [a] Classes of the LCSFM but productivity results from the pooled model.

(–5%). In addition, as previously mentioned, a 13% increase in the scale component is offset by a 10% decrease in the noise component.

Finally, we characterise the classes.[14] For all three farm types, farms belonging to the intensive class on average produce more output and are larger in terms of fixed

[14]See the descriptive statistics for each class and each farm type in Tables A1, A2 and A3 in the Appendix S1.

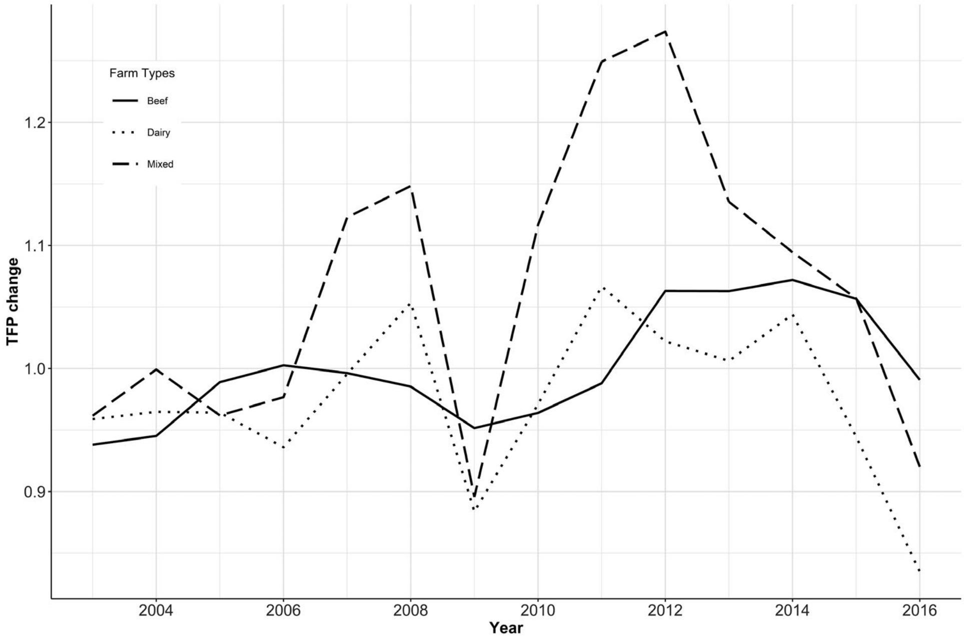

Figure 1. Cumulative TFP change over the period 2002–2016

Figure 2. Cumulative change in TFP components over the period 2002–2016

assets. They have higher intermediate consumption and higher production costs per hectare of UAA (fertilisers, pesticides) and per livestock unit (concentrated feed, veterinary costs), and receive a larger amount of operational subsidies per hectare of

UAA on average. Farms in the extensive class are on average larger in terms of UAA, and are more often enrolled in agri-environmental schemes. Herd size and number of meat beef and dairy cows are higher in the intensive class than in the extensive class, in the case of beef cattle and dairy farms. By contrast, herd size is similar across both classes in the mixed farm type. This reflects the fact that the extensive class for these farms is characterised by more meat beef cows while the intensive class has a higher number of milking cows on average. For all farm types, the share of fodder maize is relatively higher in the intensive class than in the extensive class. Again, except for beef cattle, most farms located in LFA are in the extensive class. In the case of dairy farms, we also observe that farms in the extensive class have a higher milk price but lower milk yield on average compared to the intensive class, suggesting that extensive farms produce organic milk.

5. Conclusion

We provide a methodological extension of the LCSFM to contribute to understanding of the productivity of intensive and extensive farm systems. We extend the existing LCSFM to compute productivity change using the robust transitive Färe-Primont index, which has not been done before. The application is for three types of grazing livestock farms (beef cattle, dairy, mixed) in France in 2002–2016. We use a LCSFM to identify classes of farms, based on the farms' intensity (animal stocking rate, land use in terms of grassland, capital to labour ratio), extent of participation in an agri-environmental policy scheme, and external conditions (temperature and rainfall, location in LFA, trend).

From an empirical point of view, the results about productivity change and its components show small differences between the LCSFM and the pooled model, which does not account for heterogeneity. Depending on the farm type and on the productivity change component (technical change, efficiency change, scale change, noise index), sometimes the index is overestimated and sometimes underestimated in the pooled model. However, differences between models are small, ranging from 0% to 3%. In addition, in several other cases the difference between the LCSFM and the pooled model is negligible. Comparing the performance of classes identified with the LCSFM shows that the intensive class is more technically efficient on average than the extensive class for beef cattle and dairy farms. The findings about productivity change are not so clear-cut. For dairy farms, the intensive class performs better in the sense that the productivity decrease is smaller than for extensive farms on average. In contrast, for beef cattle farms the extensive farms record the higher productivity growth on average. As for mixed farms, technical efficiency is similar for both classes on average and the productivity decrease is also similar for both classes.

Analysing the average characteristics of classes shows that, for all farm types, compared to farms in the more extensive class, farms in the more intensive class are larger in terms of output and fixed assets, but smaller in terms of UAA, they have higher production cost per ha or livestock unit, and receive more operational subsidies. Our findings also show that it is important to use contextual variables to identify technological heterogeneity: the farm location in LFA, as well as weather characteristics are significant separating variables. Mainly extensive farms are located in LFA in the case and dairy and mixed farms, while in the case of beef cattle farms mainly intensive farms are located in LFA.

Further methodological developments are necessary, however, to increase the robustness of the assessment. In particular, the issue of input endogeneity, which has been considered lately in stochastic frontier estimations with various methods, is still unaddressed in the case of the LCSFM. From another empirical perspective, the participation in agri-environmental programs needs a clear specification in line with the production frontier. Also, various empirical applications of our productivity extension are necessary to understand the patterns of productivity change between the pooled model and LCSFM, and across classes, given that observations can move from class to class in different years. About this latter point, it is worth mentioning that our model allows farms to change classes from year to year (depending on the posterior probability). This may create some artificial attrition bias in assessing the changes between classes. In other words, the results may be more reliable if farms were to permanently stay in one class. This issue deserves investigation in future research.

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Figure A1. Cumulative change in TFP and its components per class over the period 2002-2016 for beef cattle farms.

Figure A2. Cumulative change in TFP and its components per class over the period 2002-2016 for dairy farms.

Figure A3. Cumulative change in TFP and its components per class over the period 2002-2016 for mixed farms.

Table A1. Average farm characteristics for each class for beef cattle farms.

Table A2. Average farm characteristics in each class for dairy farms.

Table A3. Average farm characteristics for each class for mixed farms.

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