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Identifying and assessing intensive and extensive technologies in European dairy farming

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Abstract

In order to tackle climate change and biodiversity loss, the European Union (EU) promotes extensive farming. However, identifying such farms across countries and assessing their performance for policy purposes remains challenging. This paper combines a latent class stochastic frontier model (LCSFM) with a novel nested metafrontier approach. The resulting model enables the identification of intensive and extensive farms across countries, estimation of farm efficiency and identification of different technology gaps. Based on Farm Accountancy Data Network data of French, Irish and Austrian dairy farms,

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we find poorer environmental but better economic performance of intensive farms, compared to extensive farms. The largest productivity differences stem from technology gaps and not from inefficiency. The approach enables a more nuanced analysis of sources of inefficiency to assist policy design for future green payments in the EU.

Keywords: efficiency, dairy farms, latent class stochastic frontier, nested metafrontiers, European Union

JEL classification: C23, Q12, Q18, D24

1. Introduction

Climate change and biodiversity loss are among the main societal challenges that mankind is facing. The European Union (EU) aims to address these issues through various policy initiatives. The European Green Deal (European Commission, 2019), particularly the Farm to Fork Strategy (European Commission, 2020a) and the Biodiversity Strategy (European Commission, 2020b), put forward ambitious mid- to long-term environmental targets for the agriculture sector. Given these aims, there is a need for the EU's Common Agricultural Policy (CAP) to provide a framework that allows farmers to reduce environmental pressures and produce in a more sustainable manner. While this can be achieved through extensive farming, such a transition should not impede other goals of the CAP, namely to ensure food security and a viable income from farming.

Targeted support in this context thus requires an approach that differentiates between extensive and intensive farms across member states and compares their economic and environmental performance. This task is far from trivial. For one, agriculture in the EU is quite heterogeneous. Even farms with similar production orientation (e.g. dairy farming) may face, for example, different natural site conditions, markets or legal regulations across geographical units (e.g. countries). These framework conditions in turn shape the production processes of farms, i.e. how they transform their inputs into outputs and how to identify what may be considered as 'extensive farming'. Second, any analysis attempting to assess performance of extensive farms across EU member states requires harmonised data. The European Farm Accountancy Data Network (FADN) provides such a database. Until recently, the focus of FADN has been on the economics of agriculture, with little capacity to develop environmental indicators (Kelly *et al.*, 2018). However, when utilised in conjunction with innovative methodologies, it is possible to provide valuable information about environmental aspects of farming systems for policymakers. This paper tackles these issues by using the concept of 'technological heterogeneity', which takes both farming intensity and geographical location into account in the analysis of farm performance. Importantly, this paper provides a blueprint for the replication of the approach using the widely available FADN dataset.

Specifically, we develop a model to distinguish between intensive and extensive dairy farms and assess their performance in a cross-country context. The model integrates a latent class stochastic frontier model (LCSFM) with a novel nested metafrontier approach. This makes it possible to identify extensive and intensive farms based on easy-to-measure indicators, which are available from FADN and the Integrated Administration and Control System (IACS) of the EU. The model has the capacity to consider technological differences stemming from two distinct sources, allowing for the estimation of differences in technological productivity between individual member states as well as extensive and intensive production technologies, respectively. This information can help policymakers in developing better targeted policy instruments within the CAP. The empirical application of the model is to the dairy sector, which is of major relevance for EU agriculture as a whole and also key in addressing the overall challenges outlined above. Specifically, the focus lies on three countries with important, yet distinct dairy farming systems, namely France, Ireland and Austria.

Since its inception, the CAP has presented a range of policy instruments to promote the extensification of farms. During the 2014–2020/22 period, the primary incentives were agri-environment schemes (AES) and a greening payment. The amount of the latter was, on average, 81 Euros per hectare (ha) in Ireland in 2019 (DAFM, 2019), 80 Euros per hectare in France in 2020 (Ministère de l'Agriculture et de la Souveraineté Alimentaire, 2022) and 90 Euros per hectare in Austria in 2019 (Federal Ministry of Agriculture, Regions and Tourism, 2020a). While AES are country-specific and allow for the targeting of particular environmental issues in the member states, a greening payment was provided through the CAP Pillar I to each EU farmer if they complied with three practices to benefit the environment. These greening measures include crop diversification (at least two crops are cultivated on farms with at least 10 ha of arable land), required ratio of permanent grassland to the utilised agricultural area (UAA) (country-specific threshold) and ecological focus areas such as trees, hedges and fallow land (at least 5 per cent of the UAA for farms with at least 15 ha of arable land) (European Commission, 2023a). The second criterion, the ratio of permanent grassland to UAA, relates primarily to specialist grazing livestock farms that rely mainly on permanent grassland. However, this criterion was applied at the national and regional levels; that is to say, farmers in a specific region received the payment if the regional threshold was attained. In the CAP 2023–2027, greening payments have been replaced by eco-schemes, which provide more flexibility to individual member states in the design of green payments and have resulted in a notable diversity of measures offered across member states (Runge *et al.*, 2022).

In general, such 'green' payments aim to achieve a reduction in environmental pressures from agriculture through extensification of production while maintaining economic performance. This change in policy direction towards extensification is the subject of a large body of empirical literature, dealing with the impact of technological heterogeneity, including extensive production technologies on farm performance. For example, some studies have compared the technical efficiency of organic and conventional farms (e.g. Kumbhakar, Tsionas and Sipilainen, 2009; Mayen, Balagtas and Alexander, 2010; Latruffe and Nauges, 2014), while others identified intensive and extensive farms with LCSFM (e.g. Alvarez and Del Corral, 2010; Kellermann and Salhofer, 2014; Martinez Cillero *et al.*, 2019; Dakpo *et al.*, 2021a). The LCSFM allows an endogenous categorisation of farms into more or less intensive groups of farms, the so-called classes, and an assessment of the level and determinants of technical efficiency. However, all of these studies focused on just one country. Cross-country analyses are seldom undertaken, although one notable example is found in the work of Lakner *et al.* (2018), who combine a stochastic frontier model with stochastic metafrontiers in a cross-country analysis on the effect of diversification activities on technical efficiency in organic farming.

Against this background, our paper contributes to (i) the methodological literature on latent class stochastic frontier estimation, (ii) the empirical literature on the analysis of extensive technologies in the particular case of dairy farming and (iii) evidence-based design of future green payments in the CAP.

First, the stochastic metafrontier approach of Huang, Huang and Liu (2014) is extended to a novel nested metafrontier approach, which is combined with an LCSFM. This approach allows us to compare the technology of productivity as well as drivers of inefficiency across extensive and intensive farms and countries, respectively. This results in two types of nested metafrontiers, which essentially represent two different ways of disentangling overall efficiency. The first type of metafrontier focuses on how intensive and extensive technologies differ between countries, while the second type facilitates the investigation of common differences between extensive and intensive technologies across countries.

Our second contribution consists of the empirical application of the above described novel metafrontier approach. Specifically, we analyse specialist dairy farms in three EU countries that are important for European dairy production, namely Ireland, France and Austria, using FADN data from 2015 to 2018. In this context, we provide further findings for the empirical literature on the analysis of extensive technologies in dairy farming; these relate to separating variables for latent intensive and extensive technologies in dairy farming, productivity and efficiency, as well as drivers of inefficiency.

Our final contribution lies in the description of how our novel metafrontier approach can be used to design future green payments within the CAP and, in particular, the minimum threshold required to receive such payments. The approach particularly addresses the need for a pragmatic, yet consistent way of identifying extensive and intensive production technologies, based on data sources that are readily available across member states, namely FADN and IACS. The proposed approach can also be easily amended to use other indicators for identifying extensive technologies, as soon as better environmental indicators become available in the near future, for example via the Farm Sustainability Data Network. More generally, the approach developed can be extended to other settings of firm performance analysis, where technological heterogeneity is also assumed to arise through two distinct channels.

Our findings indicate worse environmental but better economic performance of intensive farms, compared to extensive farms in dairy farming in the three countries considered, Ireland, France and Austria, over the period 2015–2018. Against the background of the EU's Green Deal objectives and the resulting implications for the farming sector, we thus provide further evidence that productivity losses need to be expected along the way. In the case of our analysis, the largest component of lower productivity is attributable to technology gaps between countries and between the extensive and intensive technologies and not to inefficiency. Nevertheless, we identify some potential to support efficiency gains by providing farm framework conditions that enable easier access to hired labour and, at least for intensive farms, farm growth. With respect to the relationship between public payments and efficiency, our results indicate heterogeneous effects, depending on how efficiency is measured, i.e. as group efficiency or meta efficiency. One size fits all policies thus seem inadequate to mitigate productivity losses due to extensive technologies. Instead, policymakers need to consider differences between, on the one hand, member states and, on the other hand, intensive and extensive farms.

On this basis, the approach developed in this paper is also important for policy design. Future green payments within the CAP, and in particular the minimum thresholds to receive such payments, could be designed using the method proposed here in order to adequately compensate farmers for losses due to more extensive production practices. Our approach is flexible enough to incorporate 'in principle' differences between geographical units and between intensive and extensive technologies, respectively, and consequently could enable better targeted green payments. Specifically, this could be done by first re-estimating similar models with larger EU datasets across FADN farms. In the second step, the parameter estimates of the separating variables (in our case, livestock density, fodder share and rented land share) could be used for out-of-sample predictions of the most probable production technology (intensive or extensive) for all farms in IACS. Finally, eligibility for green payments could be based on whether farms are found to operate under an extensive technology or not.

The remainder of the paper is structured as follows. The next section provides some background information on dairy farming in Ireland, France and Austria and how the dairy farming systems differ between these three EU member states. The third section describes the methodology, starting with a description of the LCSFM, and then describes the conceptualisation and estimation of the novel nested metafrontiers. Next, the FADN dataset used for the analysis and the empirical specification of the model is described. The fourth section presents and discusses the results. First, an overview of the general LCSFM results is provided before focusing on results related to the nested metafrontiers. Finally, in the last section, concluding remarks regarding our empirical findings are provided, along with recommendations for the design of future EU green payments and avenues for future research.

2. Background on dairy farming in the EU countries studied: Ireland, France and Austria

Benefiting from a temperate climate with mild winters and annual rainfall between 800 and 1,200 mm, Ireland has favourable grass growth conditions in which a competitive low-cost pasture-based dairy farming sector has been developed (Thorne and Fingleton, 2006; Lapple and Cullinan, 2012; Mihailescu *et al.*, 2015). The dairy food and drink sector has expanded significantly in the post-milk quota era through targets for a 50 per cent increase in milk production and value-added processing. Dairy is Ireland's largest food and drinks export category, valued at 5.1 billion Euros in 2021 (Bord Bia, 2022).

Irish grass-based dairy farms are relatively unique in Europe since most farms operate a seasonal milk production system with compact spring calving, matching grass growth to milk production. In operating this system, the proportion of the lowest cost feed component, grazed grass, is optimised in the diet of dairy animals (Macdonald *et al.*, 2008). Dairy cows graze on pastures for most of the year, on average 240 days per year from early spring to late autumn, with 95 per cent of their diet consisting of grass (Bord Bia, 2022). Organic dairy production is a niche subsector. There were 62 organic dairy farms (out of a total of over 18,000) with an average herd size of 79 cows in 2019. This is compared to a national population of 16,700 specialist dairy farms (12 per cent of all farms) with an average herd size of 80 cows (Donnellan *et al.*, 2020). According to Lapple and Cullinan (2012), there are many reasons for the low number of organic farms in Ireland, including farmers' perceptions of organic profitability, costs of conversion, information availability and access to organic markets, amongst others.

The number of organic dairy farms in France is also low, although not as low as in Ireland. While France is the second largest producer of dairy milk in the EU, with 17 per cent of the EU milk, behind Germany (23 per cent) (Eurostat, 2021), only 4 per cent of the milk is produced under organic farming practices (certified or in conversion) (Agreste, 2020). Milk is produced in France in three main areas: around half of national production comes from plains in Western France where dairy farms are intensive with higher use of maize silage, one-third is produced by mixed crop and livestock farms in northeastern France, while the rest is produced on mountain farms (Guesdon and Perrot, 2010).

Dairy farms in France have been consistently increasing their size and specialisation, particularly since the removal of EU dairy quotas in 2015. They have also become less reliant on grassland and more on maize silage; in 2000, 42 per cent of French dairy farms' UAA had one-third of their UAA cultivated with silage maize, while the respective share of farms increased to 63 per cent in 2014 (Ministère de l'Agriculture et de l'Alimentation, 2017). These intensive farms are mainly located in Western France, while farms in the mountains produce Protected Designation of Origin cheese.

In Austria, milk is also produced in the mountains, as large parts of Austria are located in the Alps. Due to the topography and climatic conditions in these mountainous areas, agricultural landscapes are dominated by forests and permanent grassland. Farms with grazing livestock, in particular dairy farms and more extensive grazing livestock farms, are the most common farm types in these regions. In total, specialist grazing livestock farms make up around 45 per cent of all farms in Austria, of which roughly half (24 per cent) deliver milk to dairies (Federal Ministry of Agriculture, Regions and Tourism (BMLRT), 2020b). The less favourable climatic conditions and topography in mountainous areas result in a smaller average dairy farm size in Austria compared to France and Ireland. Dairy farms in Austria are mostly family farms with an average of around 22 dairy cows, with a total number of LSUs of about 36, and roughly 33 ha of UAA, mostly permanent grassland. Dual-use breeds dominate; consequently, the average annual milk yield is around 7,800 kg per dairy cow. Apart from dairy farming, these farms also often generate additional revenue from forestry and 'other gainful activities' as defined by FADN, including the provision of (machinery) services or agro-tourism (LBG, 2020).

Regarding the adoption of ecological approaches, many dairy farms in Austria have converted to organic farming as a more extensive form of agricultural production. In general, Austria has the highest share of organic farms in the EU (18.3 per cent in 2017), and the share of organic farms with milk delivery is even higher (25.5 per cent in 2017) (Federal Ministry of Agriculture, Regions and Tourism (BMLRT), 2020b). The organic farming sector in Austria experienced a dynamic development in the 1990s, shortly before and after Austria joined the EU in 1995, expanding from around 2,000 organic farms in 1992 to around 20,000 organic farms in 1998. This transition to organic farming was underpinned by government subsidies and a successful development of organic products and brands, as well as their broad acceptance by large food chains and supermarkets (Vogl and Hess, 1999). After this considerable growth period, the number of organic farms developed less dynamically, reaching around 24,000 farms in 2019 (Federal Ministry of Agriculture, Regions and Tourism (BMLRT), 2020b).

3. Data and methodology

3.1. Methodology and empirical specification

The LCSFM is used to classify farms into extensive and intensive technologies. Technically, the LCSFM estimates a mixture of production functions by exploiting the dataset's information (Parmeter and Kumbhakar, 2014).[1] Moreover, the probability of adopting a particular technology depends on farm characteristics. Explicitly, let us consider the following production function:

$$y_{it} = f(\mathbf{x}_{it}; \beta_{\mathbf{c}}) \exp\left(\text{is} \in_{it,c}\right) \tag{1}$$

1 The LCSFM has been previously discussed in Caudill (2003), Orea and Kumbhakar (2004) and Greene (2005).

where y_{it} is the output and $\mathbf{x}_{it}$ is a vector of inputs of an observation i in period t. $\boldsymbol{\beta}_\mathbf{c}$ is the vector of production function parameters when farms adopt tech- nology c. is $\epsilon_{it,c} = v_{it,c} - u_{it,c}$ and u and v are, respectively, the one-sided and two-sided error terms, with u representing the inefficiency component.

Assuming a half-normal distribution for u and a normal distribution for v, the conditional probability associated with the production function in (1) can be easily derived (see Aigner, Lovell and Schmid, 1977):

$$P(it|c) = \frac{2}{\sqrt{\sigma^2_{v,c} + \sigma^2_{u,c}}}\phi\left(\frac{\epsilon_{it,c}}{\sqrt{\sigma^2_{v,c} + \sigma^2_{u,c}}}\right)\boldsymbol{\Phi}\left(-\epsilon_{it,c}\frac{\left(\sigma_{u,c}/-\sigma_{v,c}\right)}{\sqrt{\sigma^2_{v,c} + \sigma^2_{u,c}}}\right) \tag{2}$$

where $\sigma^2_{v,c}$ is the variance associated with the two-sided error term v. $\sigma^2_{u,c}$ is, on the other hand, the variance associated with u.

The unconditional probability is obtained as

$$P(it) = \sum_{c=1}^{C} \Pi(it,c)\,P(it|c) \tag{3}$$

where $\Pi(it,c)$ is the prior probability of observation i in period t belonging to class c and is specified using a logit parametrisation:

$$\Pi(it,c) = \frac{\exp\left(\mathbf{q}_{\mathbf{it}};\boldsymbol{\lambda}_\mathbf{c}\right)}{\sum_{j=1}^{C}\exp\left(\mathbf{q}_{\mathbf{it}};\boldsymbol{\lambda}_\mathbf{j}\right)} \quad c = 1,\ldots,C;\boldsymbol{\lambda}_\mathbf{C} = 0 \tag{4}$$

$$0 \leq \Pi(it,c) \leq 1; \sum_{c}\Pi(it,c) = 1.$$

$\mathbf{q}$ is a vector of variables influencing the probability of being in a specific class, in this paper referred to as 'separating variables'.

The class membership of each observation is determined based on the posterior probability $P(c|it)$, which is defined using Bayes rule as follows:

$$P(c|it) = \frac{\Pi(it,c)\,P(it|c)}{\sum^{C}\ \Pi(it,j)\,P(it|j)} \tag{5}$$

Each observation is allocated to the class with the highest posterior probability, and the efficiency is obtained using the parameters of the corresponding class. The conditional inefficiency is obtained following Jondrow *et al.* (1982):

$$E\left[u_{it,c}|\epsilon_{it,c}\right] = \mu_{*it,c} + \sigma_{*c}\left[\frac{\phi\left(-\mu_{*it,c}/\sigma_{*c}\right)}{1-\boldsymbol{\Phi}\left(-\mu_{*it,c}/\sigma\quad\right)}\right] \tag{6}$$

where $\mu_{*it,c} = -\frac{\epsilon_{it,c}\sigma^2_{u,c}}{\sigma^2_{u,c}+\sigma^2_{v,c}}$ and $\sigma^2_{*c} = \frac{\sigma^2_{u,c}\sigma^2_{v,c}}{\sigma^2_{u,c}+\sigma^2_{v,c}}$, and efficiency is obtained with $\exp\{E[-u_{it,c}|\epsilon_{it,c}]\}$.

Finally, we also accommodate inefficiency determinants by specifying the variance parameter of the one-sided error term as $\sigma^2_{u,itc} = \exp(\mathbf{z}_{\mathbf{u,it}}; \boldsymbol{\delta}_{\mathbf{u,c}})$,[2] where $\mathbf{z}_{\mathbf{u,it}}$ is a vector of variables that are drivers of inefficiency.

A single output and five inputs describe the production technology: total farm output in Euros, UAA in ha, total farm labour in annual working unit (AWU), herd size in LSU, intermediate consumption in Euros and capital in Euros. Intermediate consumption includes variable inputs used for production, such as animal feed, seeds, pesticides, fertilizers, water and electricity. Capital is measured as the value of assets, excluding the value of livestock (since it is already accounted for in the herd size input) and the value of agricultural land (accounted for in the UAA input).

For the estimation, a Translog functional form is used:

$$\ln y_{it} = \beta_{0g|c} + \sum_{k=1}^{5} \beta_{kg|c} \ln x_{k_{it}} + \frac{1}{2}\sum_{k=1}^{5}\sum_{l=1}^{5} \beta_{klg|c} \ln x_{k_{it}} \ln x_{l_{it}} + \sum_{m=2015}^{2018} \delta_{mg|c} D_m + v_{it|c} - u_{it|c} \tag{7}$$

where D_m are time dummies and $g = \{\text{Austria, France, Ireland}\}$.

All inputs and output variables are normalised by their geometric mean. As the dairy farming system differs in each country, we allow the marginal productivity to vary per country. This implies that we allow all five inputs to have different marginal productivities for each country and within each class of farms. For this, we introduce country dummies that interact with all the coefficients of the main production function (see equation 7 and subscript g). This approach is preferable to running three independent estimations for each country, as the pooled model provides more freedom. More importantly, the classification between intensive and extensive classes is undertaken on the same basis.

The literature on intensive vs. extensive technology in dairy farming (Alvarez and Del Corral, 2010; Kellermann and Salhofer, 2014; Orea, Perez and Roibas, 2015; Dakpo *et al.*, 2021a, c) provides information on possible separating variables. The final selection of separating variables for our model is based on data availability and technological characteristics relevant in all three countries studied. Three separating variables are used: livestock density (stocking rate), calculated as the number of LSU per hectare of forage area, the ratio of fodder area to UAA and the share of the rented area to UAA. The latter is included in the separating variables on the grounds that practices are very different between farmers who operate rented land and those who own their land.[3] In particular, rented land may be an obstacle to adopting sustainable management practices or conservation behaviour (Ranjan *et al.*, 2022).

As regards the inefficiency drivers, these are selected based on the rich existing literature, particularly in relation to articles on dairy farms in EU countries

2 $\sigma^2_{v,c} = \exp(W_{v,c})$.

3 We thank the Editor for this suggestion.

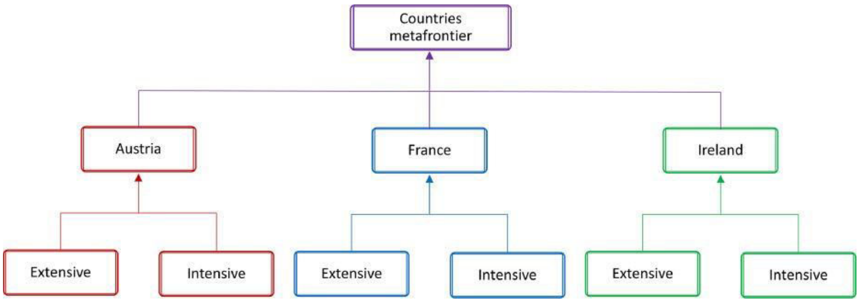

Fig. 1. Nested metafrontiers comparing countries' technologies.

(Orea, Perez and Roibas, 2015; Latruffe *et al.*, 2017; Skevas, Emvalomatis and Brummer, 2018; Bradfield *et al.*, 2021). The variables used as determinants of technical inefficiency are the ratio of hired labour to total farm labour, the farm size (in ha UAA),[4] and the value of CAP operational subsidies per LSU.

While we aim to compare the performance of farms between extensive and intensive classes and across three different countries, the efficiency scores obtained using the formula in (6) are not directly comparable due to different frontiers. For this purpose, we estimate a series of nested metafrontiers of two types. The first type of metafrontiers compares the extensive and intensive technologies in each country. This implies that three metafrontiers are estimated, one for each country. Second, the three previously estimated metafrontiers are nested into overall countries' metafrontiers, as illustrated in Figure 1. The second type of metafrontier first compares extensive technologies in the three countries and subsequently compares the intensive technologies in all the three countries. Here two metafrontiers are estimated, which are then nested into an overall intensity metafrontier as illustrated in Figure 2. The two figures represent two types of metafrontier, comparing different technologies. Therefore, in every case, the overall metafrontiers have nothing to do with each other. They rather represent different ways of calculating and disentangling overall efficiency. The first type of metafrontier puts more emphasis on comparing technologies between countries, while the second type of metafrontiers allows for the investigation of differences in common technologies across countries with respect to extensive or intensive farms.

For the estimation of the metafrontiers, we follow Huang, Huang and Liu (2014), and define the metafrontier as the production function that is common for all groups $r = 1, \ldots, R$ as follows:

$$f^{r}\left(\mathbf{x}_{it};\beta_{r}\right)=f^{M}\left(\mathbf{x}_{it};\beta_{\mathbf{M}}\right)\exp\left(-u_{it,r}^{M}\right)\quad\forall r,i,t \tag{8}$$

4 We thank one reviewer for suggesting this variable.

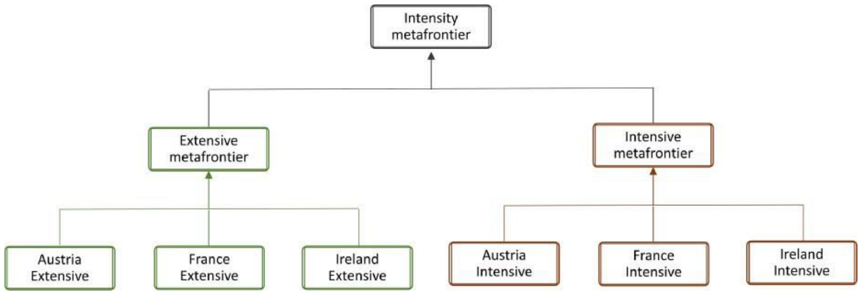

Fig. 2. Nested metafrontiers comparing extensive and intensive technologies.

where $f^M(\mathbf{x}_{it};\boldsymbol{\beta}_\mathbf{M})$ is the metafrontier and $u^M_{it,j} \geq 0$.

Hence, the technology gap ratio (TGR) can be defined as

$$TGR^r_{it} = \frac{f^r(\mathbf{x}_{it};\beta_r)}{f^M(\mathbf{x}_{it};\beta_\mathbf{M})} = \exp\left(-u^M_{it,r}\right) \tag{9}$$

A group's TGR measures the distance between the group's technology and the overall technology available to all producers. Therefore, the closer this ratio is to one, the closer the group's technology is to the overall technology. Following Huang, Huang and Liu (2014), the observed output y_{it} relative to the metafrontier $f^M(\mathbf{x}_{it};\boldsymbol{\beta}_\mathbf{M})$ is made up of three components:

$$\frac{y_{it}}{f^M(\mathbf{x}_{it};\beta_\mathbf{M})} = \frac{y_{it}}{f^r(\mathbf{x}_{it};\beta_r)} \times \frac{f^r(\mathbf{x}_{it};\beta_r)}{f^M(\mathbf{x}_{it};\beta_\mathbf{M})} = TE^r_{it} \times TGR^r_{it} \times \exp\left(v_{it,r}\right) \tag{10}$$

where TE^r_{it} is the group-specific technical efficiency and $\exp(v_{it,r})$ is the noise component.[5]

From (10) one can also derive:

$$MTE_{it,r} = \frac{y_{it}}{f^M(\mathbf{x}_{it};\beta_\mathbf{M})\exp\left(v_{it,r}\right)} = TE^r_{it} \times TGR^r_{it} \tag{11}$$

where $\mathrm{MTE}_{it,r}$ is the farm's technical efficiency with respect to the metafrontier $f^M(\mathbf{x}_{it};\boldsymbol{\beta}_\mathbf{M})$.

Battese, Rao and O'Donnell (2004) and O'Donnell, Rao and Battese (2008) suggested a mixed approach, where in the first step, the group frontiers are estimated using maximum likelihood (ML). In the second step, mathematical programming is used to estimate the metafrontier. However, this approach neglects the error in estimating $f^r(\mathbf{x}_{it};\boldsymbol{\beta}_r)$. Therefore, Huang, Huang and Liu

5 $\frac{y_{it}}{f^r(\mathbf{x}_{it};\boldsymbol{\beta}_r)} = \exp(-u_{it,r} + v_{it,r})$.

(2014) suggest estimating the metafrontier as

$$\ln \hat{f}^{r}(\mathbf{x}_{it};\beta_{r}) = \ln f^{M}(\mathbf{x}_{it};\beta_{\mathbf{M}}) - u^{M}_{it,r} + v^{M}_{it,r} \quad \forall i,t,r = 1,\ldots,R \tag{12}$$

Equation (12) is almost identical to a classic stochastic frontier regression, with the difference that the dependent variable $\hat{f}^{r}(\mathbf{x}_{it};\boldsymbol{\beta}_{r})$ is the ML estimate of the group r's specific frontier.

In our case, the metafrontier framework is extended to the classes obtained from the LCSFM and can be easily nested to account for the different countries. Let us assume now two nested metafrontiers $(M_1 \subseteq M_2)$. The first metafrontier is obtained using equation (12):

$$\ln \hat{f}^{r_1}\left(\mathbf{x}_{it};\beta_{r_1}\right) = \ln f^{M_1}\left(\mathbf{x}_{it};\beta_{\mathbf{M}_1}\right) - u^{M_1}_{it,r_1} + v^{M_1}_{it,r_1} \quad \forall i,t,r_1 = 1,\ldots,R_1 \tag{13}$$

For the second metafrontier, we suggest estimating the following equation:

$$\ln \hat{\hat{f}}^{r_2}\left(\mathbf{x}_{it};\beta_{r_2}\right) = \ln f^{M_2}\left(\mathbf{x}_{it};\beta_{\mathbf{M}_2}\right) - u^{M_2}_{it,r_2} + v^{M_2}_{it,r_2} \quad \forall i,t,r_2 = 1,\ldots,R_2 \tag{14}$$

where $\hat{\hat{f}}^{r_2}$ is the ML estimate obtained in equation (13).

The observed output y_{it} relative to the second metafrontier $f^{M_2}(\mathbf{x}_{it};\boldsymbol{\beta}_{\mathbf{M}_2})$ is made up of four components:

$$\begin{aligned}\frac{y_{it}}{f^{M_2}\left(\mathbf{x}_{it};\beta_{\mathbf{M}_2}\right)} &= \frac{y_{it}}{f^{r_1}\left(\mathbf{x}_{it};\beta_{r_1}\right)} \times \frac{f^{r_1}\left(\mathbf{x}_{it};\beta_{r_1}\right)}{f^{M_1}\left(\mathbf{x}_{it};\beta_{\mathbf{M}_1}\right)} \times \frac{f^{M_1}\left(\mathbf{x}_{it};\beta_{\mathbf{M}_1}\right)}{f^{M_2}\left(\mathbf{x}_{it};\beta_{\mathbf{M}_2}\right)} \\ &= TE^{r_1}_{it} \times TGR^{r_1}_{it} \times TGR^{r_2}_{it} \times \exp\left(v_{it,r_1}\right)\end{aligned} \tag{15}$$

We define the overall efficiency with respect to the second metafrontier as

$$MTE_{it,r_2} = \frac{y_{it}}{f^{M_2}\left(\mathbf{x}_{it};\beta_{\mathbf{M}_2}\right)\exp\left(v_{it,r_1}\right)} = TE^{r_1}_{it} \times TGR^{r_1}_{it} \times TGR^{r_2}_{it} \tag{16}$$

As shown previously, we assume that u^{M}_{it} follows a half-normal distribution with the same drivers as the group frontiers, and v^{M}_{it} follows a standard normal distribution. Relative to the previous figures, M_1 will represent each country's metafrontier in Figure 1 (Austria, France and Ireland) and extensive and intensive metafrontiers in Figure 2. M_2 will represent the overall countries metafrontier in Figure 1 and the overall intensity metafrontier in Figure 2.

3.2. Data

We use data from the FADN, a harmonised database of book-keeping information for commercial farms across the EU (European Commission, 2023b). The FADN farm survey is carried out annually in each EU Member State,

Table 1. Distribution of farms per country and year

	2015	2016	2017	2018	Total
Austria	802	739	684	681	2,906
France	1,019	976	940	883	3,818
Ireland	324	324	302	309	1,259

Data source: EU-FADN—DG AGRI.

collecting accountancy data from about 80,000 commercial farms in the EU (European Commission, 2018). This paper focuses on specialist dairy farms, on which at least two-thirds of their standard output is obtained from dairy activity (Eurostat, 2023a). The sample used contains 2,527 farms. The distribution of farms per country and for the years 2015 to 2018 in our dataset is presented in Table 1.

France has the highest number of observations, representing about 47 per cent of the total sample, followed by Austria with 37 per cent and Ireland with only 16 per cent. In terms of the evolution of dairy for all three countries, there is a slight decrease in the number of observations, following the general observation of the decrease in the number of European dairy farmers.

Table 2 describes the pooled sample used and the three countries' sub-samples.[6] Dairy farms in the Austrian sub-sample are smaller than Irish and French farms in land area (32 ha of UAA vs. 66 and 105 ha, respectively), are mainly located in mountainous areas and more than one quarter (29 per cent) are organic farms. Their smaller size is also reflected in a lower value of output compared to their Irish and French counterparts on average, with a larger share derived from other gainful activities (18 per cent, while it is close to 0 per cent and 2 per cent for Irish and French farms, respectively). Other gainful activities include activities directly related to the farm, e.g. processing of farm products, contract work, agro-tourism, production of renewable energy and forestry, with most Austrian farms including forest area. Despite their small size in terms of output, Austrian farms have a higher milk yield than Irish farms (almost similar to France) and higher productivity (in terms of total output per hectare and LSU[7]) than Irish and French farms. They receive a much higher value of operational subsidies, 611 vs. 348 (France) and 170 (Ireland) Euros per LSU. The operational subsidies considered here are CAP subsidies excluding investment subsidies. These consist mainly of decoupled payments, as well as subsidies from AES and compensating subsidies for being

6 In this analysis, all monetary values are deflated with real price indices obtained from Eurostat with base year 2010. More precisely, values of outputs, subsidies and revenues were deflated with price indices of 'Agricultural goods output, including fruits and vegetables'. Intermediate consumption and costs of inputs were deflated with price indices of 'Goods and services currently consumed in agriculture', while asset values were deflated with price indices of 'Goods and services contributing to agricultural investment'.

7 'The livestock unit, abbreviated as LSU (or LU), is a reference unit that 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' (Eurostat, 2023b).

Table 2. Descriptive statistics of the sample used pooled over the period 2015–2018

Variables	Three countries pooled		Austria		France		Ireland	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Production technology variables								
Total farm output (Euros) y	180,227	134,862	104,154	66,945	225,879	145,134	217,377	141,653
UAA (ha) x_1, Z_{u2}	72.8	56.1	32.5	22.8	105.6	58.5	66.4	35.9
Total farm labour (AWU) x_2	1.93	0.90	1.89	0.66	2.04	1.07	1.71	0.74
Herd size (LSU) x_3	95.4	72.2	42.0	25.6	120.9	68.0	141.4	83.1
Intermediate consumption (Euros) x_4	122,292	95,408	63,555	41,480	162,895	103,212	134,738	91,283
Capital excluding herd and land (Euros) x_5	447,940	300,726	549,719	297,732	365,429	273,435	463,238	312,149
Livestock density (LSU/ha of forage area) q_1	1.67	0.65	1.59	0.59	1.57	0.63	2.18	0.57
Share of fodder in UAA q_2	0.86	0.16	0.89	0.15	0.79	0.16	0.99	0.06
Share of rented land in UAA q_3	0.55	0.37	0.31	0.25	0.83	0.27	0.24	0.22
Share of hired labour in total labour Z_{u1}	0.07	0.15	0.02	0.06	0.10	0.17	0.12	0.18
Operational subsidies per LSU (Euros) Z_{u3}	415.9	274.8	611.6	319.5	348.1	157.6	169.9	69.8
Other variables								
Ratio of output from gainful activities in farm output	0.08	0.14	0.18	0.16	0.02	0.08	0.001	0.02
Ratio of dairy output to total farm output	0.68	0.15	0.60	0.15	0.74	0.12	0.69	0.11
Cost of machinery and buildings (Euros)	15,493	11,916	9,095	5,426	21,589	13,373	11,776	8,307
Cost of contracting work (Euros)	14,630	15,263	5,316	5,795	23,424	17,091	9,459	7,250
Milk yield (litres per dairy cow)	6,554	1,621	6,724	1,579	6,732	1,697	5,628	1,077
Total farm output per hectare (Euros)	2,842	1,418	3,481	1,643	2,217	986	3,265	1,120

(continued)

Table 2. (Continued)

	Three countries pooled		Austria		France		Ireland	
Variables	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Total farm output per LSU (Euros)	2,051	814	2,523	923	1,869	635	1,513	325
Total farm output per AWU (Euros)	94,852	56,141	57,868	41,558	112,402	48,259	126,991	61,770
Intermediate consumption per LSU (Euros)	1,379	540	1,575	596	1,370	480	956	252
Intermediate consumption per milk litre (Euros)	0.37	0.17	0.42	0.22	0.37	0.14	0.29	0.10
Intermediate consumption as a share of total output	0.69	0.18	0.64	0.19	0.75	0.17	0.64	0.14
Costs of fertilizers per hectare of UAA (Euros)	97.6	90.5	39.3	50.5	97.5	61.4	232.4	92.9
Costs for crop protection per hectare of UAA (Euros)	28.7	37.3	11.5	21.1	48.5	41.8	8.4	13.1
Costs of concentrate feed per LSU (Euros)	416.1	179.7	444.4	197.2	402.4	173.3	392.4	145.3
AES subsidies per LSU (Euros)	66.6	110.0	162.8	127.3	13.3	41.8	6.0	20.1
Farm income (Euros)	91,059	65,908	67,029	43,401	104,361	71,880	106,186	73,723
Farm income per AWU (Euros)	47,936	28,618	37,462	28,174	51,309	24,255	61,886	33,102
Net value added (Euros)	58,853	51,624	42,039	34,393	60,959	51,557	91,274	66,289
Net value added per AWU (Euros)	30,780	24,174	23,310	21,742	29,092	18,853	53,140	29,999
Share of farms located in LFA	0.67	0.47	0.92	0.27	0.49	0.50	0.65	0.48
Share of farms located above 600 m	0.30	0.46	0.56	0.50	0.20	0.40	0.002	0.04
Share of fully organic-certified farms	0.14	0.34	0.29	0.46	0.06	0.24	0.01	0.11
Share of partly organic farms or in conversion to organic farming	0.01	0.11	0.01	0.10	0.02	0.14	0.001	0.03

Note: Labour is measured with AWU, which are full-time equivalents. Regarding the share of fodder, forage crops include fodder roots and brassicas (mangolds, etc.), other fodder plants, temporary grass, meadows, and permanent pastures, rough grazing. Data source: EU-FADN—DG AGRI.

located in less favoured areas (LFA). The latter are mountainous areas or areas with natural constraints. Apart from LFA payments, the high value of subsidies per LSU in Austria is also explained by the role of AES subsidies, as Austria offers a very broad and well-subscribed AES with high farmer participation. AES subsidies account for 24 per cent of the CAP operational subsidies in the Austrian sub-sample, while the respective figures are 2.5 per cent and 3 per cent in the Irish and French sub-samples, respectively. Organic farming is supported as a separate measure in the Austrian AES. In addition, organic farms in the EU automatically received the CAP greening payment, irrespective of whether they complied with the three mandatory requirements. This also explains the high average value of operational subsidies per hectare in the Austrian sub-sample, where 29 per cent of the farms are fully organic-certified farms, compared to about 1 per cent in Ireland and 6 per cent in France.

On average, dairy farms in the Irish sub-sample have almost no other gainful activities, greater herd size and a higher livestock density in terms of the number of LSU per hectare of forage area than their French and Austrian counterparts. Very few Irish sample farms are organic, reflecting a national population of less than 30 certified organic dairy farms in the reference period. The Irish farms, on average, apply more chemical fertilizers per hectare than French and Austrian farms but fewer crop protection products. This is reflected in the grass-based production system, which aims to maximise low-cost grass utilisation and milk solids output per hectare (O'Brien and Hennessy, 2017). This is illustrated by Irish farms having the lowest milk yield per cow but the highest total farm output per labour unit while incurring the lowest milk production costs (intermediate consumption) per litre. These farms receive the lowest amount of subsidies per LSU on average due to the low prevalence of organic dairy farms, low AES payments and high LSU per hectare.

French dairy farms in the sub-sample have the highest UAA (105 ha) but the lowest capital value on average. This is compensated by the highest cost of external capital through contract work. These farms use the highest level of crop protection products per hectare compared to farms in the Irish and Austrian sub-samples. The French sample farms have the highest average share of the rented area in UAA (83 per cent), one reason being that land operated by farms with associates is often owned by the associates who rent it out to the farm. A lower share of farms in the French sub-sample is located in LFAs compared to the Irish and Austrian sub-samples. Only 6 per cent of the French sub-sample are organic farms, in line with the national statistics.

4. Results and discussion

Table 3 presents a summary of the LCSFM estimation results regarding the separating variables and the production functions.[8] The model is also displayed with a single class (standard stochastic frontier model) for comparison purposes.

8 All estimations were conducted using the R package {sfaR} (Dakpo, Desjeux and Latruffe, 2021b). The full estimation results can be found in Appendix Table A1.

Table 3. Summary of LCSFM estimation results

Variables	Countries	Standard model (single class)	Latent class model with two classes	
			Class 1 (extensive)	Class 2 (intensive)
Production function: Elasticities at the sample mean				
log(x_1: UAA)	Austria^{+}	−0.041*	−0.034	−0.029
	France	0.038*	0.095**	0.001
	Ireland^{+}	−0.066	−0.085	0.039
log(x_2: total farm labour)	Austria^{+}	−0.004	−0.024	0.012
	France	0.123***	0.138***	0.133***
	Ireland^{+}	−0.153***	−0.051	−0.13**
log(x_3: herd size)	Austria^{+}	0.476***	0.548***	0.309***
	France	0.178***	0.129**	0.174***
	Ireland^{+}	0.511***	0.32***	0.702***
log(x_4: intermediate consumption)	Austria^{+}	0.422***	0.525***	0.35***
	France	0.638***	0.765***	0.521***
	Ireland^{+}	0.532***	0.637***	0.286***
log(x_5: capital excluding herd and agricultural land)	Austria^{+}	0.127***	0.049	0.221***
	France	0.12***	0.038	0.192***
	Ireland^{+}	0.128***	0.254***	−0.002
Separating variables				
Stocking rate: q_1	–	–	−1.035***	–
Share of fodder area in UAA: q_2	–	–	1.398***	–
Share of rented land in UAA: q_3	–	–	−0.604***	–
Inefficiency drivers				
Share of hired labour in total labour: Z_{u1}	–	−1.752***	−0.921***	−8.315***
UAA: Z_{u2}	–	−0.009***	−0.001	−0.105***
Operational subsidies per LSU Z_{u3}	–	0.002***	0.001***	0.001***
Log-likelihood	–	2,703.8	3,142.0	
Scale elasticity at the sample means	Austria	0.98	1.064	0.863
	France	1.097	1.165	1.021
	Ireland	0.952	1.075	0.895
Average efficiency	All three countries	0.858	0.823	0.953
	Austria	0.809	0.810	0.885
	France	0.885	0.830	0.987
	Ireland	0.889	0.848	0.967
Average posterior probability	–	1	0.762	0.768

(continued)

Table 3. (Continued)

Variables	Countries	Standard model (single class)	Latent class model with two classes	
			Class 1 (extensive)	Class 2 (intensive)
Number of observations	All three countries	7,983	3,393	4,590
	Austria	2,906	1,543	1,363
	France	3,818	1,435	2,383
	Ireland	1,259	415	844

Note: *, ** and *** indicate significance at the 10, 5 and 1 per cent levels, respectively.Standard errors obtained using the delta method. Data source: EU-FADN—DG AGRI.

The coefficients for the separating variables show that a higher livestock density and share of rented area in total UAA decrease the probability of belonging to class 1. In contrast, a higher percentage of fodder area in total UAA increases the likelihood of belonging to class 1. Therefore, class 1 contains farms that are more extensive on average in terms of these three indicators than farms in class 2. Accordingly, class 1 is labelled the extensive class and class 2 the intensive class in what follows.

Overall, 42.5 per cent of the whole sample is allocated to the extensive class, while 57.5 per cent of the observations are classified as intensive. Ireland appears to be the country with the most intensive farms (67 per cent), while 62.4 per cent of the farms in France are in the intensive class. Of the three countries, only Austria has more observations in the extensive class compared to the intensive one (53.1 per cent and 46.9 per cent, respectively).

The elasticity at the sample means is presented for each country for both classes (extensive and intensive) in Table 3. All elasticities are positive and statistically significant for herd size and intermediate consumption. In all three countries, the intermediate consumption elasticity is higher for the extensive class compared to the intensive class. While the elasticity of herd size is higher in the extensive class in Austria, it is the opposite in France and Ireland. In the case of area (UAA) and capital assets, when statistically significant, the elasticities are positive. UAA is statistically significant only in the case of extensive farms in France. For the capital assets, the elasticities are positive in the case of intensive farms in Austria and France.

Labour input is not statistically significant in Austria, while it is positive and statistically significant in France. In Ireland, however, labour has a negative and statistically significant effect on the sample mean in the case of the intensive class. Overall differences between the classes and the countries are presented in Table 3, confirming the relevance of estimating the technology with different marginal productivities for the countries.

Table 3 also displays the estimation results of the inefficiency drivers. A negative sign reveals a negative impact of the driver on technical inefficiency and thus a positive impact on technical efficiency. Results indicate that using hired labour is associated with higher technical efficiency in both the extensive and intensive classes. This suggests a positive effect of farming in general on job creation in rural areas and confirms the finding of Bradfield *et al.* (2021) for Irish dairy farms and of Latruffe *et al.* (2017) for dairy farms in nine EU countries. Farm size increases technical efficiency, which is also in line with Bradfield *et al.* (2021), but only in the case of intensive farms. The impact of subsidies per LSU on inefficiency is statistically significant for both the extensive and intensive classes. This indicates that farms receiving more subsidies per LSU are less efficient than other farms. This finding is in line with a large part of the literature investigating subsidies (Latruffe *et al.*, 2017; Minviel and Latruffe, 2017; Skevas, Emvalomatis and Brummer, 2018; Dakpo *et al.*, 2021a) and is confirmed here for both extensive and intensive farms.

Table 3 shows that the intensive class is, on average, more technically efficient than the extensive class. In the case of France and Ireland, the intensive classes are almost fully efficient (0.987 and 0.967, respectively). This is in line with other performance indicators, as shown in Table 4 (results by country can be found in Appendix Tables A2–A4). On average, the extensive class has statistically lower total output per hectare, per LSU and per AWU. The extensive class also has lower milk yield, lower farm income and net value added than the intensive class in each of the three countries. As underlined by Kellermann and Salhofer (2014), permanent grassland (which is included as fodder in the separating variables) is less productive than maize silage in terms of energy content, which may partly explain the lower performance of the extensive class compared to the intensive class in the results. Table 4 also shows that both classes differ in terms of livestock density and ratio of fodder area and in terms of reliance on chemical inputs. The extensive class uses on average less fertilizer per hectare and crop protection products per hectare, confirming its extensive label. By contrast, the extensive class receives higher subsidies per LSU than the intensive class, including higher AES subsidies per LSU. This may be due to organic AES payments, since the extensive class has a higher share of organic farms than the intensive class (19 per cent vs. 10 per cent in the three countries pooled, 32 per cent vs. 26 per cent in Austria, 9 per cent vs. 4 per cent in France and 2 per cent vs. 1 per cent in Ireland). Finally, the differences between the intensive and extensive class are also reflected in terms of site conditions. Results in Table 4 show that 84 per cent of farms in the extensive class are located in LFA regions, while for the intensive class, it is only 55 per cent. This also translates into differences in efficiency. Intensive farms located in LFA regions are less efficient than intensive farms outside LFA regions (0.93 vs. 0.98). Interestingly, for extensive farms, the difference is much smaller (0.82 vs. 0.83).

Regarding the metafrontiers, a summary of the results can be found in Tables 5–8.[9] As described in the methodology section and depicted

9 The metafrontier production functions' estimation can be found in Appendix Tables A5 and A6.

Table 4. Characteristics of extensive and intensive classes for the three countries pooled

Variables	Class 1 (Extensive)	Class 2 (Intensive)	t test of equality (Sign.)
Total farm output (Euros) y	121,283	223,800	***
UAA (ha) x_1, Z_{u2}	63.7	79.5	***
Total farm labour (AWU) x_2	1.82	2.02	***
Herd size (LSU) x_3	71.1	113.3	***
Intermediate consumption (Euros) x_4	90,849	145,536	***
Capital excluding herd and land (Euros) x_5	413,868	473,127	***
Livestock density (LSU/ha of forage area) q_1	1.34	1.92	***
Share of fodder in UAA q_2	0.92	0.81	***
Share of rented land in UAA q_3	0.46	0.61	***
Share of hired labour in total labour Z_{u1}	0.05	0.09	***
Operational subsidies per LSU (Euros) Z_{u3}	520.6	338.5	***
Ratio of output from gainful activities in farm output	0.10	0.06	***
Ratio of dairy output to total farm output	0.68	0.68	
Cost of machinery and buildings (Euros)	12,781	17,498	***
Cost of contracting work (Euros)	10,144	17,946	***
Milk yield (litres per dairy cow)	5,971	6,987	***
Total farm output per hectare (Euros)	2,290	3,250	***
Total farm output per LSU (Euros)	1,885	2,174	***
Total farm output per AWU (Euros)	67,964	114,728	***
Intermediate consumption per LSU (Euros)	1,410	1,356	***
Intermediate consumption per milk litre (Euros)	0.42	0.34	***
Intermediate consumption as a share of total output	0.77	0.64	***
Costs of fertilizers per hectare of UAA (Euros)	65.6	121.2	***
Costs for crop protection per hectare of UAA (Euros)	14.3	39.3	***
Costs of concentrate feed per LSU (Euros)	403.7	425.3	***
AES subsidies per LSU (Euros)	94.5	46.0	***
Farm income (Euros)	61,395	112,987	***
Farm income per AWU (Euros)	33,965	58,264	***
Net value added (Euros)	34,722	76,691	***

(continued)

Table 4. (Continued)

Variables	Class 1 (Extensive)	Class 2 (Intensive)	*t* test of equality (Sign.)
Net value added per AWU (Euros)	18,792	39,642	***
Share of farms located in LFA	0.84	0.55	***
Share of farms located above 600 m	0.45	0.18	***
Share of fully organic-certified farms	0.19	0.10	***
Share of partly organic farms or in conversion	0.02	0.01	***

Note: *** indicates significance at the 1 per cent level. Data source: EU-FADN—DG AGRI.

Table 5. Results for extensive and intensive classes with respect to the countries' metafrontiers

		Austria's metafrontier	France's metafrontier	Ireland's metafrontier
$TE_{it}^{r_1}$	Extensive class' average	0.810	0.830	0.848
	Intensive class' average	0.885	0.987	0.967
$TGR_{it}^{r_1}$	Extensive class' average	0.825	0.923	0.961
	Intensive class' average	0.961	0.968	0.983
MTE_{it,r_1}	Extensive class' average	0.669	0.766	0.816
	Intensive class' average	0.851	0.956	0.952

Data source: EU-FADN—DG AGRI.

in Figure 1, the first type of metafrontiers is based on calculating country-specific metafrontiers for intensive and extensive farms in the first step and an overall metafrontier for all countries in the second step (Tables 5 and 6). In contrast, the second type of metafrontier depicted in Figure 2 is based on first calculating a metafrontier for extensive and intensive farms, respectively, across countries and then an overall metafrontier for intensive and extensive farms together (Tables 7 and 8).

Table 5 reveals a higher TGR with respect to the country-specific metafrontier for the intensive class, whatever the country. This indicates that the intensive farms' frontier is closer to the overall frontier available in each country. In other words, the intensive class is more productive than the extensive class in all three countries. Comparing the different countries in Table 6 shows that, overall, France has the highest productivity compared to Austria and Ireland. Moreover, although Ireland has a very high group-specific technical efficiency (0.928) and at the same time a high TGR with respect to its country frontier (0.976), the meta efficiency is relatively low (0.624). The reason for this is that the Irish technology is further away from the overall frontier of all countries, as can be seen from the TGR with respect to the metafrontier for all

Table 6. Results for the three countries with respect to the overall three countries frontier

		Overall countries metafrontier
$TE_{it}^{r_1}$	Average for Austria's farms	0.845
	Average for France's farms	0.928
	Average for Ireland's farms	0.928
$TGR_{it}^{r_1}$	Average for Austria's farms	0.889
	Average for France's farms	0.951
	Average for Ireland's farms	0.976
$TGR_{it}^{r_2}$	Average for Austria's farms	0.587
	Average for France's farms	0.771
	Average for Ireland's farms	0.684
$MTEr_2$	Average for Austria's farms	0.450
	Average for France's farms	0.687
	Average for Ireland's farms	0.624

Data source: EU-FADN—DG AGRI.

Table 7. Results for the three countries with respect to the extensive and intensive metafrontiers

		Extensive metafrontier	Intensive metafrontier
$TE_{it}^{r_1}$	Average for Austria's farms	0.810	0.885
	Average for France's farms	0.830	0.987
	Average for Ireland's farms	0.848	0.967
$TGR_{it}^{r_1}$	Average for Austria's farms	0.980	0.938
	Average for France's farms	0.970	0.970
	Average for Ireland's farms	0.943	0.954
MTE_{it,r_1}	Average for Austria's farms	0.793	0.830
	Average for France's farms	0.806	0.958
	Average for Ireland's farms	0.801	0.923

Data source: EU-FADN—DG AGRI.

countries (0.684). Austria has the lowest meta efficiency (0.450), as its country frontier is even further away from the overall countries frontier than Ireland (0.587) and farms are also farther away from their country frontier (0.889).

Table 7 displays the results of the metafrontiers estimated for extensive and intensive classes. Comparison of the extensive technologies across the countries through their TGRs reveal that Austria has the most productive extensive technology (0.980), while comparing the intensive technologies, France has the best intensive technology (0.970). Finally, Table 8 shows that, as in the case of each country, the intensive technology is overall more productive than the extensive technology (0.568 vs. 0.398). The main reason for this is that the metafrontier of extensive farms is further away from the overall frontier (0.497)

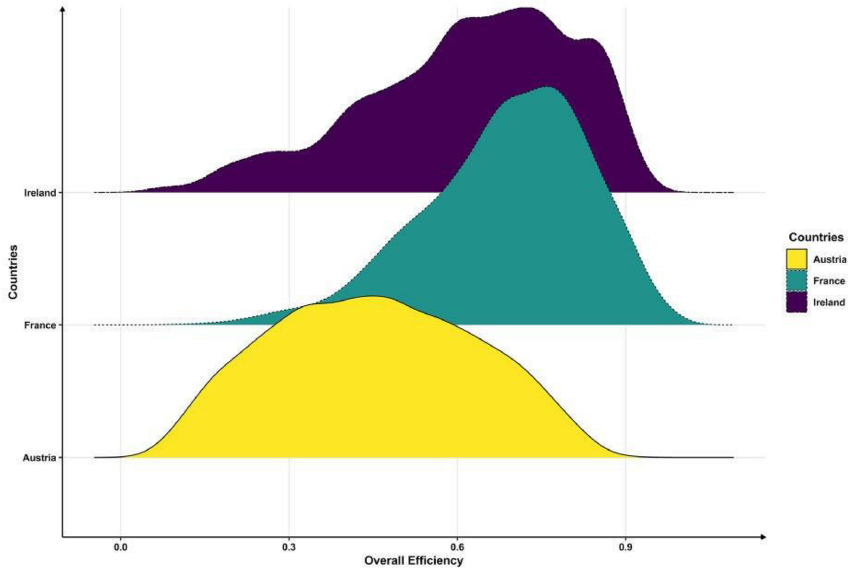

Fig. 3. Distribution of overall efficiency per country. Data source: EU-FADN—DG AGRI.

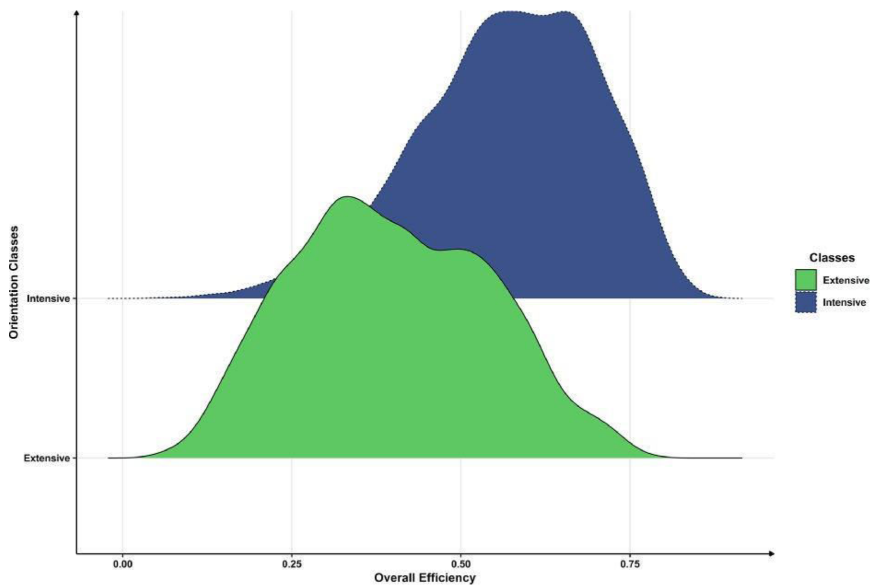

Fig. 4. Distribution of overall efficiency between extensive and intensive farms. Data source: EU-FADN—DG AGRI.

Table 8. Results for the intensive and extensive classes with respect to the overall intensity frontier

		Overall metafrontier
$TE_{it}^{r_1}$	Extensive class' average	0.823
	Intensive class' average	0.953
$T\quad GR_{it}^{r_1}$	Extensive class' average	0.972
	Intensive class' average	0.960
$TGR_{it}^{r_2}$	Extensive class' average	0.497
	Intensive class' average	0.619
$MTEr_2$	Extensive class' average	0.398
	Intensive class' average	0.568

Data source: EU-FADN—DG AGRI.

than that of intensive farms (0.619). Finally, Figures 3 and 4 show the distribution of the meta efficiency with respect to the two overall frontiers (one for the countries and one for the production intensity). The two figures provide a more detailed representation of the differences in efficiency. For example in Figure 3, it can be seen that the distributions in France and Ireland are both left-skewed, while in Austria it is rather symmetrical.

We can also assess the drivers of inefficiency with respect to the metafrontiers (estimation results are presented in Appendix Tables A5 and A6). Looking at the country-based metafrontiers, it can for example be seen that an increase in farm size is associated with higher meta efficiency across all countries and also with respect to the countries' overall metafrontiers. Looking at the metafrontiers based on extensive and intensive farms across countries, farm size in terms of UAA shows a statistically significant positive effect on meta efficiency for intensive farms only. Finally, with respect to operational subsidies per LSU, we find a positive association with meta efficiency, based on the common frontier of extensive farms. For intensive farms, there is no statistically significant effect, while for the overall intensity-based metafrontier, we find a negative effect.

5. Conclusions

This paper used a method that can easily and statistically classify farms as extensive or intensive, namely the LCSFM and combined this classification with a novel nested metafrontier approach. The method was applied to dairy farms in Ireland, France and Austria, with homogeneous book-keeping data from the EU-FADN from 2015 to 2018. Using three easy-to-measure indicators (share of fodder area in UAA, livestock density and share of rented land), the analysis identified intensive and extensive specialist dairy farms. The latter farms not only differ in terms of these indicators (extensive farms have a lower livestock density, a higher share of fodder area and a lower share of rented land), but also use fewer pesticides and chemical fertilizers. This method thus allows for the identification of thresholds of the three above-mentioned indicators to define classes of farms depending on their degree of intensive technology. It also enables the identification of performance gaps between classes in terms of technical efficiency and different technology gaps using an original metafrontier approach.

Overall, the nested metafrontier approach allows for a more nuanced analysis of sources of inefficiency, as efficiency can be decomposed into three parts: group efficiency and two TGRs, related either to metafrontiers of countries or extensive and intensive farms. Both types of metafrontiers and analyses of drivers based on these metafrontiers provide valuable information for policymakers. The analysis reveals that the largest share of lower productivity is attributable to technology gaps between countries and between the extensive and intensive technology and not to inefficiency. However, the analysis of drivers of inefficiency undertaken suggests potential for some efficiency gains. Such potential could be a support by policymakers through the provision of framework conditions for farms that enable easier access to hired labour and, at least for intensive farms, farm growth. With respect to subsidies, our results also suggest different effects depending on how efficiency is measured. Additionally, for extensive farms, subsidies appear to concurrently have a negative effect on group efficiency and a positive effect on meta efficiency, measured with respect to the metafrontier of all extensive farms. Policymakers thus need to consider these heterogenous effects and possible trade-offs between supporting efficiency gains and reducing a technology gap when designing policy measures aimed at supporting productivity of farms.

Against the background of the EU's Green Deal objectives and the resulting implications for the farming sector, our results provide further evidence that productivity losses must be expected along the way. Additionally, one size fits all policies would appear to be inadequate to mitigate these productivity losses. Rather, policies aimed at enhancing productivity of farms need to consider differences between member states as well as intensive and extensive farms. This is consistent with recent research by Renner, Sauer and El Benni (2021), which arrived at similar conclusions, suggesting that extensive and intensive production technologies in dairy farming are largely linked to local natural production conditions and public payments adapted to local site conditions, as well as additional income sources that may be decisive for the successful implementation of extensification strategies on farms.

The method developed in this paper also has specific importance for policy design. Future green payments within the CAP, and in particular the minimum thresholds to receive such payments, could be designed using the method proposed here in order to adequately compensate farmers for losses due to more extensive production practices. The methodological approach developed here is flexible enough to incorporate 'in principle' differences between countries and intensive and extensive technologies, respectively, and could consequently facilitate better targeting of green payments. Specifically, this could be done by first re-estimating similar models to the one presented in this paper with larger EU datasets of FADN farms. In the second step, the parameter estimates of the separating variables (in our case, livestock density, fodder share and rented land share) could be used for out-of-sample predictions of the most probable production technology (intensive or extensive) for all farms in the IACS. This is, however, only possible if the selected separating variables are also available in IACS data. Finally, eligibility for green payments could be based on whether farms have adopted extensive production technology or not.

We acknowledge some limitations of our study, which is a first illustration of the usefulness of the LCSFM to disentangle intensive and extensive technologies across different countries or regions and could be refined in future research. First, extensification, including conversion to organic farming, may, in particular, be a successful adaptative strategy to improve resilience in the context of increased changing economic conditions such as higher market volatility, end of dairy quotas or the COVID-19 crisis and may bring temporary inefficiency (Bouttes, Darnhofer and Martin, 2019; Darnhofer, 2021; Adamie and Hansson, 2022). Although the performance indicators measured here (technical efficiency, partial productivities, income and technology gaps) show that the economic performance of extensive farms is lower than that of intensive farms, this is shown for a four-year period only and may not be the case in the longer run. Further research could therefore analyse a more extended time period to investigate not only differences but also variability (e.g. vulnerability to price shocks) of performance for intensive and extensive dairy farms, as well as changes on farms over time between the two identified production technologies. In addition, unobserved heterogeneity could be controlled with the help of individual effects and panel data.

Another limitation lies in the existing FADN data where identification of intensive or extensive production technologies can only be achieved using proxies. While our analysis shows that such proxies have the discriminatory capacity to identify intensive and extensive production technologies and can provide helpful insights in the medium to long run, FADN data should be complemented by additional indicators to more clearly identify extensive farming systems and their farming practices. However, in the quest for such indicators, costs and benefits must be weighed up (Kelly *et al.*, 2018). Second, further applications could implement a matching approach in the existing modelling framework to better control for structural differences, as proposed, e.g. by Lakner *et al.* (2018).

Finally, while a transition to more extensive production technologies can contribute to the sustainability of agriculture by tackling biodiversity loss and mitigating nutrient losses to water and greenhouse gas emissions within the EU, this may also have adverse effects at a global level. A decrease in the productivity of EU agriculture could increase worldwide food prices (Beckman *et al.*, 2020). It could also increase environmental pressure from agriculture in other parts of the world with less comprehensive environmental regulations. Such aspects go far beyond the scope of this analysis but need to be considered in future research.

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Appendix

Table A1. Full estimation results of the standard stochastic frontier and LCSFM

Variables	Standard model (single class)	Class 1 (extensive)	Class 2 (intensive)
(Intercept)	0.196***	0.098***	0.179***
$\log(x_1)$	0.038*	0.095**	0.001
$\log(x_2)$	0.123***	0.138***	0.133***
$\log(x_3)$	0.178***	0.129**	0.174***
$\log(x_4)$	0.638***	0.765***	0.521***
$\log(x_5)$	0.12***	0.038	0.192***
$I(0.5 \times \log(x_1)\wedge 2)$	−0.191***	−0.146*	−0.007
$I(0.5 \times \log(x_2)\wedge 2)$	0.054*	0.212**	−0.058
$I(0.5 \times \log(x_3)\wedge 2)$	0.071	0.051	0.032
$I(0.5 \times \log(x_4)\wedge 2)$	0.085**	−0.043	0.156***
$I(0.5 \times \log(x_5)\wedge 2)$	−0.035**	−0.11***	0.043*
$I(\log(x_1) \times \log(x_2))$	−0.041*	−0.12**	−0.03
$I(\log(x_1) \times \log(x_3))$	−0.046	−0.104	−0.003
$I(\log(x_1) \times \log(x_4))$	0.063**	0.051	−0.015
$I(\log(x_1) \times \log(x_5))$	0.123***	0.192***	0.061**
$I(\log(x_2) \times \log(x_3))$	0.061**	0.12*	0.014
$I(\log(x_2) \times \log(x_4))$	−0.012	−0.015	0.046
$I(\log(x_2) \times \log(x_5))$	−0.021	−0.086***	0.029
$I(\log(x_3) \times \log(x_4))$	−0.111***	−0.007	−0.091**
$I(\log(x_3) \times \log(x_5))$	0.028	0.007	0.034
$I(\log(x_4) \times \log(x_5))$	−0.088***	−0.042	−0.136***
factor(YEAR)2016	−0.073***	−0.091***	−0.058***
factor(YEAR)2017	−0.001	−0.016	0.02**
factor(YEAR)2018	−0.018**	−0.029**	0.005
factor(COUNTRY)Ireland	−0.109***	0.017	−0.157***
factor(COUNTRY)Austria	−0.005	0.132***	−0.115***
$\log(x_1)$:factor(COUNTRY)Ireland	−0.104**	−0.18**	0.038
$\log(x_1)$:factor(COUNTRY)Austria	−0.079**	−0.129**	−0.03
$\log(x_2)$:factor(COUNTRY)Ireland	−0.276***	−0.188**	−0.264***
$\log(x_2)$:factor(COUNTRY)Austria	−0.127***	−0.161***	−0.121***
$\log(x_3)$:factor(COUNTRY)Ireland	0.334***	0.191*	0.529***
$\log(x_3)$:factor(COUNTRY)Austria	0.298***	0.419***	0.135*
$\log(x_4)$:factor(COUNTRY)Ireland	−0.106*	−0.129	−0.235**
$\log(x_4)$:factor(COUNTRY)Austria	−0.217***	−0.24***	−0.171***
$\log(x_5)$:factor(COUNTRY)Ireland	0.008	0.217***	−0.194**
$\log(x_5)$:factor(COUNTRY)Austria	0.007	0.011	0.029
$I(0.5 \times \log(x_1)\wedge 2)$:factor(COUNTRY)Ireland	0.201**	0.003	0.286*

(continued)

Table A1. (Continued)

Variables	Standard model (single class)	Class 1 (extensive)	Class 2 (intensive)
I(0.5 × log(x_1)∧2):factor(COUNTRY)Austria	0.072	0.067	−0.015
I(0.5 × log(x_2)∧2):factor(COUNTRY)Ireland	−0.238***	−0.603***	−0.031
I(0.5 × log(x_2)∧2):factor(COUNTRY)Austria	−0.074*	−0.212**	0.105
I(0.5 × log(x_3)∧2):factor(COUNTRY)Ireland	−0.292*	−0.251	−0.692***
I(0.5 × log(x_3)∧2):factor(COUNTRY)Austria	0.717***	0.352**	0.656***
I(0.5 × log(x_4)∧2):factor(COUNTRY)Ireland	−0.133	0.438*	−0.538***
I(0.5 × log(x_4)∧2):factor(COUNTRY)Austria	0.386***	0.387***	0.373***
I(0.5 × log(x_5)∧2):factor(COUNTRY)Ireland	0.061	0.647***	−0.337*
I(0.5 × log(x_5)∧2):factor(COUNTRY)Austria	0.087***	0.153***	−0.018
I(log(x_1) × log(x_2)):factor(COUNTRY)Ireland	−0.054	0.397***	−0.074
I(log(x_1) × log(x_2)):factor(COUNTRY)Austria	0.005	0.115	0.021
I(log(x_1) × log(x_3)):factor(COUNTRY)Ireland	−0.028	0.37**	−0.206
I(log(x_1) × log(x_3)):factor(COUNTRY)Austria	0.016	0.186**	−0.017
I(log(x_1) × log(x_4)):factor(COUNTRY)Ireland	0.013	−0.246	−0.03
I(log(x_1) × log(x_4)):factor(COUNTRY)Austria	−0.011	−0.091	0.024
I(log(x_1) × log(x_5)):factor(COUNTRY)Ireland	−0.046	−0.205	0.003
I(log(x_1) × log(x_5)):factor(COUNTRY)Austria	−0.071**	−0.146***	−0.007
I(log(x_2) × log(x_3)):factor(COUNTRY)Ireland	0.217***	−0.34**	0.401***
I(log(x_2) × log(x_3)):factor(COUNTRY)Austria	−0.09*	−0.318***	0.056
I(log(x_2) × log(x_4)):factor(COUNTRY)Ireland	0.012	0.276*	−0.199**
I(log(x_2) × log(x_4)):factor(COUNTRY)Austria	0.022	0.148*	−0.182***
I(log(x_2) × log(x_5)):factor(COUNTRY)Ireland	−0.012	0.146	−0.11
I(log(x_2) × log(x_5)):factor(COUNTRY)Austria	0.033	0.09*	−0.008
I(log(x_3) × log(x_4)):factor(COUNTRY)Ireland	0.178	0.056	0.541***
I(log(x_3) × log(x_4)):factor(COUNTRY)Austria	−0.502***	−0.334***	−0.528***
I(log(x_3) × log(x_5)):factor(COUNTRY)Ireland	0.008	−0.008	0.114
I(log(x_3) × log(x_5)):factor(COUNTRY)Austria	−0.127***	−0.079	−0.117**
I(log(x_4) × log(x_5)):factor(COUNTRY)Ireland	−0.045	−0.498***	0.242*
I(log(x_4) × log(x_5)):factor(COUNTRY)Austria	0.074**	−0.051	0.192***
factor(YEAR)2016:factor(COUNTRY)Ireland	0.045***	0.049*	0.038**
factor(YEAR)2017:factor(COUNTRY)Ireland	0.003	0.007	−0.008
factor(YEAR)2018:factor(COUNTRY)Ireland	−0.061***	−0.087***	−0.057**
factor(YEAR)2016:factor(COUNTRY)Austria	0.086***	0.081***	0.073***
factor(YEAR)2017:factor(COUNTRY)Austria	0.029**	0.009	0.041**
factor(YEAR)2018:factor(COUNTRY)Austria	0.107***	0.093***	0.106***
Inefficiency drivers			
*Zu*_(Intercept)	−3.314***	−3.335***	−0.835***
Z_{u1}	−1.752***	−0.921***	−8.315***

(continued)

Table A1. (Continued)

Variables	Standard model (single class)	Class 1 (extensive)	Class 2 (intensive)
Z_{u2}	−0.009***	−0.001	−0.105***
Z_{u3}	0.002***	0.001***	0.001***
2-Sided error term			
Zv_(Intercept)	−4.142***	−5.349***	−4.327***
Separating variables			
q_(Intercept)		0.656	–
q_1		−1.035***	–
q_2		1.398***	–
q_3		−0.604***	–

Note: *, ** and *** indicate significance at the 10, 5 and 1 per cent levels, respectively. Data source: EU-FADN—DG AGRI.

Table A2. Characteristics of extensive and intensive classes in Austria

Variables	Class 1 (Extensive)	Class 2 (Intensive)	t test of equality (Sign.)
Total farm output (Euros) y	78,280	133,444	***
UAA (ha) x_1, Z_{u2}	30.8	34.3	***
Total farm labour (AWU) x_2	1.84	1.95	***
Herd size (LSU) x_3	34.6	50.4	***
Intermediate consumption (Euros) x_4	53,308	75,156	***
Capital excluding herd and land (Euros) x_5	518,544	585,011	***
Livestock density (LSU/ha of forage area) q_1	1.33	1.88	***
Share of fodder in UAA q_2	0.94	0.83	***
Share of rented land in UAA q_3	0.27	0.36	***
Share of hired labour in total labour Z_{u1}	0.01	0.02	***
Operational subsidies per LSU (Euros) Z_{u3}	697.1	514.8	***
Ratio of output from gainful activities in farm output	0.19	0.17	***
Ratio of dairy output to total farm output	0.61	0.60	
Cost of machinery and buildings (Euros)	8,341	9,948	***
Cost of contracting work (Euros)	4,165	6,619	***
Milk yield (litres per dairy cow)	6,313	7,189	***
Total farm output per hectare (Euros)	2,867	4,176	***
Total farm output per LSU (Euros)	2,289	2,787	***
Total farm output per AWU (Euros)	45,260	72,142	***
Intermediate consumption per LSU (Euros)	1,610	1,534	***
Intermediate consumption per milk litre (Euros)	0.46	0.37	***

(continued)

Table A2. (Continued)

Variables	Class 1 (Extensive)	Class 2 (Intensive)	*t* test of equality (Sign.)
Intermediate consumption as a share of total output	0.71	0.57	***
Costs of fertilizers per hectare of UAA (Euros)	24.45	56.15	***
Costs for crop protection per hectare of UAA (Euros)	5.21	18.56	***
Costs of concentrate feed per LSU (Euros)	423.3	468.3	***
AES subsidies per LSU (Euros)	186.4	136.1	***
Farm income (Euros)	49,428	86,954	***
Farm income per AWU (Euros)	28,381	47,743	***
Net value added (Euros)	27,166	58,877	***
Net value added per AWU (Euros)	15,313	32,363	***
Share of farms located in LFA	0.96	0.87	***
Share of farms located above 600 m	0.68	0.44	***
Share of fully organic-certified farms	0.32	0.26	***
Share of partly organic farms or in conversion	0.01	0.01	**

Note: ** and *** indicate significance at the 5 and 1 per cent levels, respectively. Data source: EU-FADN—DGAGRI.

Table A3. Characteristics of extensive and intensive classes in France

Variables	Class 1 (Extensive)	Class 2 (Intensive)	*t* test of equality (Sign.)
Total farm output (Euros) y	157,656	266,961	***
UAA (ha) x_1, Z_{u2}	99.1	109.5	***
Total farm labour (AWU) x_2	1.85	2.15	***
Herd size (LSU) x_3	98.7	134.2	***
Intermediate consumption (Euros) x_4	127,235	184,369	***
Capital excluding herd and land (Euros) x_5	317,434	394,332	***
Livestock density (LSU/ha of forage area) q_1	1.21	1.79	***
Share of fodder in UAA q_2	0.87	0.74	***
Share of rented land in UAA q_3	0.75	0.88	***
Share of hired labour in total labour Z_{u1}	0.08	0.12	***
Operational subsidies per LSU (Euros) Z_{u3}	425.1	301.6	***
Ratio of output from gainful activities in farm output	0.03	0.02	***
Ratio of dairy output to total farm output	0.77	0.72	***

(continued)

Table A3. (Continued)

Variables	Class 1 (Extensive)	Class 2 (Intensive)	*t* test of equality (Sign.)
Cost of machinery and buildings (Euros)	18,418	23,499	***
Cost of contracting work (Euros)	17,240	27,148	***
Milk yield (litres per dairy cow)	5,827	7,277	***
Total farm output per hectare (Euros)	1,638	2,565	***
Total farm output per LSU (Euros)	1,602	2,030	***
Total farm output per AWU (Euros)	84,862	87	***
Intermediate consumption per LSU (Euros)	1,326	1,396	***
Intermediate consumption per milk litre (Euros)	0.41	0.34	***
Intermediate consumption as a share of total output	0.85	0.69	***
Costs of fertilizers per hectare of UAA (Euros)	74.2	111.6	***
Costs for crop protection per hectare of UAA (Euros)	26.44	61.7	***
Costs of concentrate feed per LSU (Euros)	386.1	412.3	***
AES subsidies per LSU (Euros)	20.1	9.3	***
Farm income (Euros)	71,543.8	124,122.93	***
Farm income per AWU (Euros)	37,694.5	59,507.2	***
Net value added (Euros)	35,647.4	76,200.9	***
Net value added per AWU (Euros)	17,840.7	35,867.3	***
Share of farms located in LFA	0.72	0.35	***
Share of farms located above 600 m	0.35	0.10	***
Share of fully organic-certified farms	0.09	0.04	***
Share of partly organic farms or in conversion	0.03	0.01	***

Note: *** indicates significance at the 1 per cent level. Data source: EU-FADN—DG AGRI.

Table A4. Characteristics of extensive and intensive classes in Ireland

Variables	Class 1 (Extensive)	Class 2 (Intensive)	*t* test of equality (Sign.)
Total farm output (Euros) y	155,397	247,853	***
UAA (ha) x_1, Z_{u2}	63.5	67.8	**
Total farm labour (AWU) x_2	1.63	1.75	***
Herd size (LSU) x_3	111.5	156.1	***
Intermediate consumption (Euros) x_4	104,613	149,551	***
Capital excluding herd and land (Euros) x_5	358,131	514,920	***

(continued)

Table A4. (Continued)

Variables	Class 1 (Extensive)	Class 2 (Intensive)	*t* test of equality (Sign.)
Livestock density (LSU/ha of forage area) q_1	1.80	2.37	***
Share of fodder in UAA q_2	0.99	0.99	**
Share of rented land in UAA q_3	0.17	0.27	***
Share of hired labour in total labour Z_{u1}	0.10	0.14	***
Operational subsidies per LSU (Euros) Z_{u3}	194.6	157.8	***
Ratio of output from gainful activities in farm output	0.00	0.00	
Ratio of dairy output to total farm output	0.66	0.70	***
Cost of machinery and buildings (Euros)	9,800	12,747	***
Cost of contracting work (Euros)	7,835	10,258	***
Milk yield (litres per dairy cow)	5,193	5,842	***
Total farm output per hectare (Euros)	2,401	3,690	***
Total farm output per LSU (Euros)	1359	1,590	***
Total farm output per AWU (Euros)	93,946	14,3239	***
Intermediate consumption per LSU (Euros)	960	954	
Intermediate consumption per milk litre (Euros)	0.33	0.27	***
Intermediate consumption as a share of total output	0.72	0.60	***
Costs of fertilizers per hectare of UAA (Euros)	189.1	253.6	***
Costs for crop protection per hectare of UAA (Euros)	6.27	9.38	***
Costs of concentrate feed per LSU (Euros)	391.7	392.7	
AES subsidies per LSU (Euros)	10.3	3.9	***
Farm income (Euros)	70,798	123,587	***
Farm income per AWU (Euros)	41,832	71,746	***
Net value added (Euros)	59,613	106,842	***
Net value added per AWU (Euros)	35,013	62,053	***
Share of farms located in LFA	0.78	0.59	***
Share of farms located above 600 m	0	0.002	
Share of fully organic-certified farms	0.02	0.01	
Share of partly organic farms or in conversion	0	0.001	

Note: ** and *** indicate significance at the 5 and 1 per cent levels, respectively. Data source: EU-FADN—DGAGRI.

Table A5. Countries' specific metafrontiers and overall metafrontier

Variables	Austria metafrontier	France metafrontier	Ireland metafrontier	Overall countries metafrontier
(Intercept)	0.134***	0.203***	0.062***	0.622***
$\log(x_1)$	−0.09***	0.015*	−0.097***	−0.201***
$\log(x_2)$	0.001	0.149***	−0.12***	0.073***
$\log(x_3)$	0.4***	0.151***	0.552***	0.24***
$\log(x_4)$	0.391***	0.58***	0.483***	0.267***
$\log(x_5)$	0.165***	0.146***	0.099***	−0.036***
$I(0.5 \times \log(x_1) \wedge 2)$	−0.072***	−0.07***	0.127***	−0.158***
$I(0.5 \times \log(x_2) \wedge 2)$	0.017	0.054**	−0.186***	−0.052
$I(0.5 \times \log(x_3) \wedge 2)$	0.713***	0.097***	−0.392***	0.117
$I(0.5 \times \log(x_4) \wedge 2)$	0.482***	0.151***	−0.061	0.264***
$I(0.5 \times \log(x_5) \wedge 2)$	0.041***	0.0002	0.012	−0.278***
$I(\log(x_1) \times \log(x_2))$	−0.038**	−0.046***	−0.048	0.074**
$I(\log(x_1) \times \log(x_3))$	0.009	−0.042***	−0.049	−0.084*
$I(\log(x_1) \times \log(x_4))$	0.043***	0.029*	0.087**	0.26***
$I(\log(x_1) \times \log(x_5))$	0.047***	0.103***	0.048	0.3***
$I(\log(x_2) \times \log(x_3))$	0.03	0.035***	0.267***	−0.036
$I(\log(x_2) \times \log(x_4))$	−0.049**	0.011	−0.036	0.089**
$I(\log(x_2) \times \log(x_5))$	0.008	−0.008	−0.02	−0.054***
$I(\log(x_3) \times \log(x_4))$	−0.615***	−0.137***	0.127**	−0.139***
$I(\log(x_3) \times \log(x_5))$	−0.085***	0.036***	0.084	−0.152***
$I(\log(x_4) \times \log(x_5))$	0.017	−0.112***	−0.155***	−0.087***
factor(YEAR)2016	0.01***	−0.066***	−0.03***	−0.08***
factor(YEAR)2017	0.037***	0.01***	0.004	−0.012
factor(YEAR)2018	0.094***	−0.004**	−0.064***	0.001
Inefficiency drivers				
Zu_(Intercept)	−2.845***	−4.836***	−1.252*	−0.027
Z_{u1}	−0.595	−0.165	−6.182**	0.905***
Z_{u2}	−0.081***	−0.019***	−0.128***	−0.021***
Z_{u3}	0.002***	0.003***	0.002	−0.0002
Two-sided error term				
Zv_(Intercept)	−6.373***	−7.143***	−6.155***	−2.566***

Note: *, ** and *** indicate significance at the 10, 5 and 1 per cent levels, respectively. All standard errors are obtained using the sandwich robust to heteroscedasticity variance–covariance matrix. Data source: EU-FADN—DG AGRI.

Table A6. Extensive and intensive specific metafrontiers and overall metafrontier

Variables	Extensive metafrontier	Intensive metafrontier	Overall metafrontier
(Intercept)	0.163***	0.192***	0.817***
$\log(x_1)$	−0.086***	−0.026***	−0.088***
$\log(x_2)$	0.088***	0.084***	−0.03
$\log(x_3)$	0.26***	0.16***	0.004
$\log(x_4)$	0.675***	0.544***	0.15***
$\log(x_5)$	0.17***	0.185***	−0.006
$I(0.5 \times \log(x_1)\wedge 2)$	0.005	0.018**	−0.025
$I(0.5 \times \log(x_2)\wedge 2)$	0.071***	−0.002	0.12*
$I(0.5 \times \log(x_3)\wedge 2)$	0.194***	0.305***	−0.294***
$I(0.5 \times \log(x_4)\wedge 2)$	0.227***	0.298***	−0.195**
$I(0.5 \times \log(x_5)\wedge 2)$	0.01**	0.037***	0.069**
$I(\log(x_1) \times \log(x_2))$	−0.017	0.021***	−0.044
$I(\log(x_1) \times \log(x_3))$	−0.096***	−0.047***	0.047
$I(\log(x_1) \times \log(x_4))$	0.055***	−0.0001	0.018
$I(\log(x_1) \times \log(x_5))$	0.038***	0.058***	−0.001
$I(\log(x_2) \times \log(x_3))$	−0.04***	0.045***	0.154**
$I(\log(x_2) \times \log(x_4))$	0.07***	−0.007	−0.088
$I(\log(x_2) \times \log(x_5))$	−0.055***	−0.034***	−0.062*
$I(\log(x_3) \times \log(x_4))$	−0.215***	−0.267***	0.212***
$I(\log(x_3) \times \log(x_5))$	0.116***	0.007	−0.099**
$I(\log(x_4) \times \log(x_5))$	−0.168***	−0.088***	0.06
factor(YEAR)2016	−0.046***	−0.041***	−0.003
factor(YEAR)2017	−0.011***	0.023***	−0.023
factor(YEAR)2018	0.009***	0.017***	−0.059***
Inefficiency drivers			
Zu_(Intercept)	−3.485***	−4.757***	−0.717***
Z_{u1}	−0.279	−0.659	−0.037
Z_{u2}	−0.009	−0.15**	−0.0004
Z_{u3}	−0.006***	0.0002	0.001***
Two-sided error term			
Zv_(Intercept)	−6.077***	−7.211***	−1.434***

Note: *, ** and *** indicate significance at the 10, 5 and 1 per cent levels, respectively. All standard errors are obtained using the sandwich robust to heteroscedasticity variance–covariance matrix. Data source: EU-FADN—DG AGRI.