Master's Thesis in Economics

Achieving Economic and Environmental Performances: the case of Protected Designation of Origin farms in France.

원산지보호명칭이 경제와 환경 부문에 미치는 영향 분석 - 프랑스 사례를 중심으로

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Achieving Economic and Environmental Performances: the case of Protected Designation of Origin farms in France.

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Abstract

Achieving Economic and Environmental Performances: the case of Protected Designation of Origin farms in France.

This paper assesses the environmental and economic performances of Protected Designation of Origin dairy farms in France. Four indicators are retained: gross profit and gross Greenhouses Gases emissions, both expressed on a per liter of milk and per hectare basis. The average GHG emission of our sample of PDO farms in Savoy and Franche-Comté amounts to 1.05 kg CO2eq per L and the profit is 0.35€ per L. Over the 118 farms of our sample, we identify by cluster analysis 70 double performing farms. Using a classification tree, we uncover that these farms have economies of scale, their cows have their first calf earlier, use less mineral fertilizers or fuel and have higher cereals and corn yields. The double performing farms maintain more biodiversity per hectare, have a higher livestock density and herd's renewal. Using an econometric model we identify practices that can act as levers of environmental and/or economic performances in PDO dairy production. The key farms' characteristics and practices that define the best a double performant farm are a low mineral fertilizers use but a high organic one and a low fuel consumption per ha. Performing farms have more permanent pastures and longer rotation on their temporary pastures, as well as a lower livestock density.

Keywords : *Protected Designation of Origin, Greenhouse Gases emission, economic performance, dairy farms*

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본 논문은 프랑스의 원산지 지정(Protected Designation of Origin, PDO) 낙농농가의 환경적, 경제적 성과를 평가하며, 이를 위해 총 수익과 온실가스 배출량을 우유 1 리터(L) 당과 1 헥타르(ha) 당 단위 등 4 가지 지표를 기준으로 살펴본다. 먼저, 프랑스 사부아(Savoie) 지방과 프랑쉬 꽁떼(Franche-Comté) 지방에 위치한 PDO 낙농농가의 평균 온실가스 배출량은 리터(L) 당 1.05kg 이며, 총 수익은 리터 당 0.35 유로(€)인 것으로 나타났다. 본 논문에서는 약 118 개의 분석대상 낙농농가에 대한 군집분석(cluster analysis)을 실시하여 이 중 약 70 개를 'double performing'농가로 분류하였다. 분류 나무(Classification Tree)를 활용하여 분석한 결과 'double performing' 농가는 규모의 경제(economies of scale) 특성이 있고, 첫 송아지를 일찍 낳는 경향을 보이며, 광물 비료나 연료를 덜 사용하고, 곡물(cereal)및 옥수수 수확량이 높은 것으로 나타났다. 또한, 이들 농가는 헥타르 당 생물다양성과 가축 밀도 및 개체 증식 속도(herd's renewal)가 높은 것으로 나타났다. 나아가 본 연구는 계량경제모형을 활용해 PDO 낙농농가의 환경적, 경제적 성과를 향상시키는 요인을 살펴보았다. 분석 결과, 성과가 가장 좋은 PDO 낙농농가는 광물 비료 사용량이 낮고, 유기농 비료 사용량이 높았으며, 헥타르 당 연료 소비량이 낮은 것으로 나타났다. 또한, 이들 농가는 더 넓은 방목초지를 가지고 있고, 일시적 초지(temporary pasture) 사용기간도 더 길었으며, 초지 당 가축 사육 밀도도 더 낮은 것으로 나타났다.

키워드: 원산지지정, 온실가스 배출, 경제적 성과, 낙농업

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1. Introduction

Designing policies to promote a reduction of the Greenhouse Gases (GHG) emissions of agricultural products is an important challenge as the agricultural sector is responsible for 13.5% of GHG emissions in the world and almost 20% in France (Pellerin S., Bamière L., Angers D., Béline F., Benoît M., Butault J.P., Chenu C., Colnenne-David C., De Cara S., Delame N., Doreau M., Dupraz P., Faverdin P., Garcia-Launay F., Hassouna M., Hénault C., Jeuffroy M.H., Klumpp K., Metay A., Moran D., 2013). As the livestock sector is accountable for 80% of the agricultural GHG emissions (Gerber, P.J., Steinfeld, H., Henderson, B., Mottet, A., Opio, C., Dijkman, J., Falcucci, A. & Tempio, 2013) and as the demand for dairy products is growing internationally, the question of a sustainable milk production sector is crucial, especially in the European Union (EU) which plans to reduce its agricultural GHG emissions by 40 to 49% before 2050 (European Commission, 2011).

In this context, the question of how and at which cost GHG emissions can be reduced has a central role. In this paper, we aim to identify future development paths for sustainable dairy farming in developed countries, with the example of milk production in two mountainous regions of France, Alps and Jura.

In addition, the abolishment of milk quotas has driven raw milk prices down in France since 2015, which in turn threatens the profitability of milk producers (Salou, van der Werf, et al., 2017). In this context, a sustainable shift of livestock farming practices needs to imply both an enhancement of economic viability and a reduction of negative environmental impacts. As stated by (Kiefer, Menzel, & Bahrs, 2014), to create a strong enough acceptance of new sustainable agricultural practices by the farmers themselves, profitability of milk production should be increased and GHG emissions should be reduced simultaneously. The

milk crisis since 2015 is also a social crisis, as many farmers quit livestock rearing because of the fall of milk prices. This phenomena is accentuated in mountainous area, where agricultural abandonment was already taking place (Hinojosa, Napoléone, Moulery, & Lambin, 2016).

In this situation, we propose to study the development of Protected Designation of Origin (PDO) farming as a transition toward a more sustainable agriculture, through the example of two PDO regions in France, Rhône-Alpes (RA) in the Alps and Franche-Comté (FC) in the Jura range, where PDO milk is produced to be transformed by cooperatives in PDO cheese. As PDO milk from these areas consistently sells at a 29% higher price than conventional milk, PDO farmers can run a profitable farm even if their production capacity is limited by the PDO requirements (Lamarque & Lambin, 2015).

Also, as PDO milk has to meet specific requirements, these regional farming systems are more extensive than the average dairy farm in France or the EU (Hocquette & Gigli, 2005; Kop, Sautier, & Eds, 2006). Indeed, cows must graze as soon as the climatic conditions allow it, the livestock density is restricted to 0.8 to 1 cow per hectare of forage (which pasture and forage corn) and the use of fertilizers is limited. These requirements naturally make the PDO milk production extensive, and so potentially more environmental friendly than the conventional milk production. As it uses fewer artificial inputs such as concentrates and fertilizers, and because it maintains pastures with higher soil carbon sequestration than croplands, these extensive farming systems are sometimes seen as environmentally performant (Haas, Wetterich, & Köpke, 2001; O'Brien, Capper, Garnsworthy, Grainger, & Shalloo, 2014; Salou, Le Mouël, & van der Werf, 2017). Nevertheless, other authors consider that intensive farming is more environmental friendly as the GHG emissions per unit of output is lower. Indeed, in intensive farming systems, cows are fed with protein rich concentrates which reduces the

enteric fermentation and therefore methane emissions per unit of dry matter intake (Guerci et al., 2013). As the cows in intensive farming also produce more milk than the ones in extensive systems, the GHG emissions per liter - total GHG emissions of the farm divided by milk production - can be lower. In a nutshell, there is no consensus on the environmental performance of extensive vs intensive farming, and the answer strongly depends on agricultural practices (Dollé, Moreau, & Foray, 2013). Another rationale justifying to study the farms sharing a common production situation is that, in France, the variability inside each production situation –intensive or extensive - is greater than the variations between production situations (Gac A. Agabriel J. Dollé J.-B., 2014). Thus, there exists a knowledge gap in explaining the variability of the farms' performances sharing the same situation. Furthermore, depending on which environmental and economic performances' indicators are chosen (GHG emission and gross profit, per liter or per hectare, in our study) and on the inclusion or not of carbon sequestration (net GHG emissions), both intensive and extensive dairy farming can be described as environmentally performant (Meier et al., 2015). We intend to evaluate to which extent PDO farming systems fare in this debate, compared to other already studied farming system, mainly organic and conventional ones (Garnett et al., 2017).

In this paper, we analyze the link between – economic performance – net result per liter of milk produced and per hectare– and environmental performance – gross GHG emissions of milk, also per liter and per hectare. We firstly analyze the correlation between environmental and economic performances' indicators, following (Jan, Dux, Lips, Alig, & Dumondel, 2012). It shows an overall synergy between economic and environmental performance on a per liter basis, and an overall trade-off on a per hectare basis.

In a second step, we identify clusters of PDO farmers according to their environmental and economic performances. Two groups of farmers - high profitability & high GHG emissions, low profitability & high GHG emissions and so on - are defined. We then investigate which agricultural or managerial practices

explain that some farmers are economically and environmentally performant and some other farmers are not (van der Werf, Kanyarushoki, & Corson, 2009). By doing so, we isolate the practices that allow farmers to be performing in both environmental and economic aspects (Micha et al., 2017).

In a last step, we investigate directly which of the farms' characteristics or practices significantly influence the environmental performance, the economic one or both simultaneously.

2. Literature Review

2.1. DEA Analysis and the computation of efficiency scores

In agricultural economics, the issue of the environmental and economic performances, and the links between them, has been analyzed with several types of methods. The most widespread one, data envelopment analysis (DEA) using distance function, is a non-parametric method which compute efficiency scores, where the most efficient decision-making unit (DMU), i.e. farm, is considered perfectly efficient (efficiency score of 1) and the efficiency scores of the other farms are obtained by comparing them to the most efficient DMU (efficiency scores strictly between 0 and 1). In the DEA framework, built on the theory of distance functions, the efficiency scores are computed as the minimum inputs bundle a farm uses to produce a given output (input distance function), divided by the inputs bundle the most efficient farm uses to produce the same amount of output (Chung, Y. Färe, 1995). This method is the most commonly used in agricultural economics because only information on the inputs and outputs of each farms is needed and DEA is therefore more flexible and less restrictive than the classical econometrics models which require the definition of a functional form for the production function (Dakpo, Jeanneaux, & Latruffe, 2016b). However, DEA can also be performed using directional distance functions, in which case the efficiency scores obtained are not radial anymore but absolute measures. In the papers using this method, the absolute economic efficiency score are usually harmonized using an absolute measure of the environmental pressures (GHG emissions), which yields a relative eco-efficiency score (Gómez-Limón, Picazo-Tadeo, & Reig-Martínez, 2012; T. Kuosmanen & Kortelainen, 2005).

Moreover, the DEA can be built without using prices or the same unit for the inputs or outputs, as long as each input or output is expressed in the same unit for each farm. In the recent development of DEA models, efforts have been put in

developing ways to integrate negative environmental externalities (e.g. GHG emissions) in the production efficiency calculation. A first solution is to consider GHG emissions as a weakly disposable input, necessary to the production process. As the DEA algorithm minimizes the inputs needed to produce a given output, it identifies farms which minimize GHG emissions for a given output level (De Koeijer, Wossink, Struik, & Renkema, 2002). Another approach considers the GHG emissions as a bad output, which is negatively recorded in the outputs bundle. As DEA can also be seen as the maximization of the output distance function, i.e. the maximum output a given inputs bundle can produce, the algorithm reduces the amount of GHG emissions to obtain an overall higher outputs bundle (Cherchye, Rock, & Walheer, 2014; Timo Kuosmanen & Podinovski, 2009). A last innovation to the DEA framework is the by-production approach, i.e. the introduction of two sub-technologies to model of the production function, one technology producing the good output and one producing the bad output, with both using the same input bundles. In this case, two efficiency score are computed for each DMU, an operational one for with the first sub-technology and an environmental one for with the second sub-technology (Dakpo, Jeanneaux, & Latruffe, 2016a; Murty, Robert Russell, & Levkoff, 2012; Ray, Mukherjee, & Venkatesh, 2018).Then, once environmental and economic efficiency scores are computed, correlation tests can be used to check if the most economically efficient farms are also the most environmentally efficient ones or not. Dakpo H. et al., (2016a) uses the latter approach and reveals that in the case of French sheep meet farming, most of the environmental inefficiency comes from the mix of inputs used (herd's size, fertilizers, feed), and that the potential for improvement in environmental efficiency is higher than the potential for improvement in economic efficiency. In the case of olive farming in Spain, (Gómez-Limón et al., 2012) finds that the environmental inefficiency is also due to a lack of technical efficiency, related to an overuse of inputs, especially polluting ones (fertilizers and concentrate feed).

The main limit of the DEA method is that while it efficiently ranks the relative performance of farms, it does not identify the drivers of performance. As

the example of Dakpo et al., (2016a) shows, the results from a DEA cannot identify drivers of efficiency that do not relate directly to the production process. Indeed, only information on the overuse/underuse of some inputs can be detected, and managerial and agricultural practices or farmers' knowledge cannot be observed. Therefore, few guidelines can be extracted from this kind of analysis to advise farmers and policy-makers on sustainable farming practices (T. Kuosmanen & Kortelainen, 2005). To bridge this gap, a logistic or Tobit regression model can be applied, with the efficiency scores as the dependent variable, to identify the drivers of performance from a set of farms' characteristics and practices (K. Hervé Dakpo and Laure Latruffe, 2016). Another issue rises from the fact that DEA is a non-parametric method and so no hypothesis tests can be performed unless bootstrap is used to obtain confidence intervals.

2.2. Econometric estimation of the economic performance using the environmental performance as explanatory variable

A second methodology uses econometrics technics to regress the environmental performance and the farm's practices and characteristics on the economic performance. In these studies, the environmental performance is regarded as a choice of farmers, predetermined before the production process. It is then treated as an exogenous explanatory variable, fixed (not related to the stochastic disturbance terms of the model) and not determined nor correlated with the other explanatory variables influencing the economic performance (Castineira & Nunes, 1999). This theoretical assumption about the exogeneity of the environmental performance is used to eliminate the endogeneity of the environmental performance, which could be correlated with the errors terms otherwise as they both are, without the above correction, determined by the other independent variables (farm's characteristics and practices). Then, an ordinary least squares regression could be run to compute the influence of both the environmental

performance and the other farm's variables on the economic performance (Choi & Helmberger, 1993). But, even if this method would eliminate most of the endogeneity risks, the results would only tell us if the environmental performance has a significant positive or negative relationship with the economic performance, not which variables influence the strength and direction of this relationship.

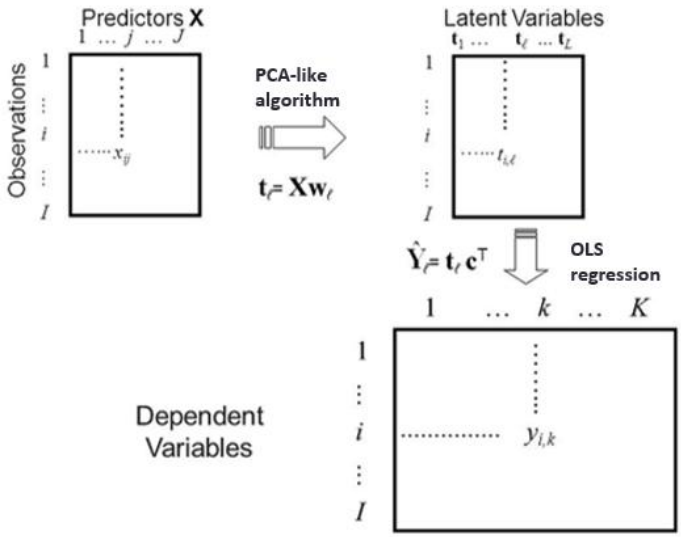
2.3. PLS regression and analysis of the impacts of the farms characteristics and practices on several performances' indicators

A third methodology is based on the Partial Least Squares (PLS) regression and is generally used when consistent datasets are available, with numerous variables for both the determination of the GHG emissions of milk and the profitability of the farms. In the existing literature on the relationships between the economic and environmental performances of dairy farms, two articles use this approach to answer a similar question in Ireland (O'Brien, Hennessy, Moran, & Shalloo, 2015) and the Netherlands (Thomassen, Dolman, van Calker, & de Boer, 2009). In both articles, the environmental performance's indicator is computed using a Life Cycle Assessment (LCA) method, computing the GHG emissions of the entire production process of the milk, for the cradle to the gate, including the GHG emissions due to the production of the concentrate, electricity, fuel or fertilizers used on the farm. The economic performance indicator is extracted from FADN data.

A PLS regression is ideally used to predict a set of dependent variables using a large set of covariates. When facing a large set of covariates in a regression model, multicollinearity problems are likely to arise as the covariates may easily be correlated. To overcome this, the PLS regression model is built upon a Principal Component Analysis (PCA) which transformed the covariates into orthogonal principal components, or uncorrelated variables, which eliminates the multicollinearity issue (Figure 1). However, a simple PCA is designed to replace

the correlated variables by principal components that represent the best the original set of covariates. The pitfall is that these new components may be little correlated with the dependent variables, and a regression run with the components could be less conclusive. In a regression framework, the principal components need to be related to the original covariates but also to explain as much as possible the variation of the dependent variables (Garthwaite, 1994). That is why the PLS regression is built on a specific algorithm which eliminates the correlation between the components of the original covariates, called here latent variables, and maximizes the correlation between the latent variables and the dependent variables. Precisely the PLS algorithm looks for a set of latent factors that simultaneously decompose the dependent variables and the covariates, under the constraint that they must explain as much as possible of the covariance between the dependent variables and the covariates (Abdi, 2010). At the end of the PLS algorithm, a new uncorrelated set of covariates, the latent variables (matrix U), is obtained with the insurance that these new variables will be as much correlated with the dependent variables as possible and that the multicollinearity between the original covariates has been withdrawn.

Figure 1: PLS framework



In the papers considered, the dependent variables analyzed are the several correlated couples of environmental and economic performances indicators. The independent variables used in the PLS regression are the farms' characteristics and agricultural practices such as the farm's and herd's sizes, the amount of concentrate feed used, milk productivity per cow, annual milk production, energy, fuel and fertilizer uses or the labor requirements.

While the PLS transformation is useful for *control variables* such as pedo-climatic conditions, it introduces unnecessary complexity in estimating the confidence intervals of estimators for the *variables of interest*. Also, this method is mainly developed to deal with multicollinearity which does not introduce bias in the estimations. The main problem arising from multicollinearity can be a smaller predictive power of the regression model as the standard errors of the coefficient are larger and thus their confidence intervals are wider.

2.4. Cluster analysis and between clusters' comparison

A last methodology has also been employed to analyze the links between environmental and economic performances, clustering the farms by their environmental performance (Fiore, Spada, Contò, & Pellegrini, 2018) or by farm characteristics (Micha et al., 2017) and then performing multiple correlation tests between the environmental and economic performances in each group. As the correlation coefficient may differ among the clusters, some information on the relationship between GHG emissions of milk and farm profitability can be obtained with this method. In this Irish case for example, Micha et al. (2017) construct 3 clusters, one with the most intensive and productive farms, one with the more extensive and less productive ones, mainly situated in Less Favored Areas (LFA) and a last cluster in between. They find out that the two extreme clusters, the most intensive and the most extensive ones, are both economically and environmentally performant, but for different reasons. Indeed, the intensive farms, as already explained, use concentrate-rich diet and so emit less methane and produce more milk. On the opposite side, extensive farms take advantage of grazing to reduce their costs and so increase their margin (economic performance), while no depending on polluting inputs such as concentrate or fertilizers. In Italy, Fiore et al., (2018) choose to cluster farms by their environmental performance (GHG emissions) and find 3 clusters, with a positive correlation in each cluster between profitability and GHG emissions. So, in this case, practicing an extensive farming is not beneficial for the farms' economic viability and an intensive farming is not environmentally sustainable.

Through the above literature review, we have presented the various methods used for analyzing the relationships between environmental and economic performances of dairy farms. There are three knowledge gaps that we intend to fill in this study:

1) To go beyond the intensive vs extensive comparison by working on a homogeneously extensive "production situation", where the bio-physical and socio-economical drivers of the environmental and economic performances are common to all farms (Lechenet, Makowski, Py, & Munier-Jolain, 2016). In a specific production situation, as the external setting of the farms is homogenous, an analysis of the drivers of the performance will isolate the managerial and agricultural practices that explain the difference in performance among the farms. By doing so, we intend to uncover tangible drivers, farming practices, that can be used as leverage for future agricultural policies.

2) The absence of a research on the specific case of PDO dairy farms. Indeed, the PDO farms studied obtain a price premium, partly related to their extensive management, which may change drivers of economic and environmental performance compared to conventional farms.

3) We use a mix of descriptive – clustering – and more causal – seemingly unrelated regression – methods to analyze the relationships between environmental and economic performances.

3. Data

In our case of two French PDO regions, we use the GHG emissions of each kg of PDO fat-and-protein corrected milk (FPCM), as an indicator of environmental performance: the lower the GHG emissions per kg FPCM, the higher the environmental performance. As an economic indicator, we selected the gross profit per liter of FPCM, the higher the profit is, the more economically performant the farmers are. For simplicity, we refer to the per kg FPCM measure as per liter.

To estimate the GHG emissions of PDO milk, we use a survey of 118 farms, financed by the PDO consortia between 2013 and 2015 (Michaud, 2016; Perrard, 2016). Gross GHG emissions - without carbon sequestration in the soil - of milk are computed using CAP'2ER, a GHG emissions calculator developed by *Institut de l'Elevage* and following Life Cycle Assessment (LCA) guidelines (Institut de L'Elevage, 2013). The LCA methodology, which computes all the cradle-to-farm gate GHG emissions is the most commonly used methodology to estimate the impacts of milk on the environment (Gerber, P., Vellinga T., Opio C., Henderson B., and Steinfeld, 2010). Indeed, the holistic definition of system's boundary (cradle-to-farm gate) on which the computation is done considers the GHG emissions due to the milk production on farm, enteric digestion, fertilizers, fuel and energy use but also the GHG emissions due to the production of the concentrate feed or fertilizers and their importance to the farm.

The gross profit is the difference between the farm's revenue and its costs, without taking into account taxes or subventions. The former includes the revenues from the sale of PDO milk, animals, cereals and roughage. Factor costs include feed, fertilizer, electricity and fuel, contracted work and animals for the renewal of the herd. To estimate the gross profit per liter, we used the information contained in the French Farm Accountancy Network Database (FADN) from 2013 to 2015

which gathers the economic and financial information of 7,293 representative farms, whose gross values added are above 25,000€ per year. This sample contains 108 dairy farms from the FC region and 94 dairy farms from the RA region. The wealth of the information collected as inputs for CAP'2ER allows us to reconstruct farms' profits, using the FADN data to estimate prices for the outputs and inputs of the farms and the CAP'2ER information as inputs and outputs' quantity.

To control for economies of scale from the farm's or the herd's sizes, as well as the degree of intensification, we also compute both the GHG emissions and the profit measure per hectare (area-based indicators) in addition to the per liter indicators (product-based indicators) (Halberg, Van Der Werf, Basset-Mens, Dalgaard, & De Boer, 2005).

Within this list of input variable to CAP'2ER, one also finds detailed information on farmers' practices and farms' characteristics, such as the farm's and herd's sizes, the amount of concentrate feed used, the cereals produced and used on farm, the fertilizer use or the labor use. These variables will be used as independent variables for the statistical analysis following the clustering of the farms (SM 1).

4. Methodology

4.1. Economic performance reconstitution

To compute the gross profit for each farm, the FADN information is used to estimate the prices of most inputs and outputs to the production process, the quantities of which are available from the surveys with the following exceptions:

- Since FADN does not identify whether a farm is PDO certified, the price of PDO milk for each year and each PDO area comes from (Ministère de l'Agriculture et de l'Alimentation, 2017);
- The prices of fertilizers and concentrates, which cannot be derived directly from FADN, is obtained from (Eurostat, 2017).
- The buying and selling prices of dairy cows, reformed cows and heifers is gathered from (Ministère de l'Agriculture et de l'Alimentation, 2015)

With this information on the price of outputs and inputs of the farms, the revenue and the factor costs for each farm are estimated and the profit computed. To test the robustness of this reconstruction, the average reconstructed profit is compared to the average reported profit for dairy farms in the Franche-Comté and Rhône-Alpes region from FADN. As the PDO farms and the FADN samples do not have the same size, we use a quota sampling of the FADN's farms so that the number of farms sampled in 2013, 2014 and 2015 and from the Franche-Comté and the Savoy regions are the same in both samples.

4.2. Clustering

4.2.1 Cluster determination

In a first step of the statistical analysis, we cluster the farms based their environmental and economic performances. Using hierarchical k-means clustering, several clusters will be identified, using the GHG emissions and profit per L as clustering variables, and the R packages "factoextra" (Kassambra & Mundt, 2017) and "NbClust" (Charrad, Ghazzali, Boiteau, & Niknafs, 2014). Hierarchical k-means clustering is an algorithm which first performs an agglomerative hierarchical clustering in order to select endogenously the optimal number of clusters and to define the centroids that will be used for the k-mean clustering afterwards. Based on the results of the agglomerative hierarchical clustering, the centroids of the clusters can be obtained and used as for the k-means algorithm which minimizes the within sum of square (WSS) in each cluster. Mathematically, if we have $X_i,\ i = 1, 2 \ldots 118$, observations of the environmental and economic performance and two clusters $C_k, k = 1,2 \ldots$ k the X_i observations will be assigned to the C_k clusters so that $\sum_k^2 \sum_{Xi \in C_k}^{118} (X_i - \mu_k)^2$, the WSS, is minimized, with μ_k being the centroid of the C_k cluster.

4.2.2. Drivers of the appurtenance to a given cluster

Once each farm is associated to one of the clusters, we aim at understanding which characteristics drive the appurtenance of farms to a given cluster. As the clustering is based on the environmental and economic performances, the fact that these performances differ between the clusters is already known. However, some of the farms' characteristics and practices (Table 1) might differ between the two clusters and are uncovered using multiples t-tests.

Nevertheless, the results of this method do not take into account the interactions and correlations between the farms' characteristics and practices (the explanatory variables). To capture the influence of each characteristics or practices simultaneously on a farm's belonging to the double performant cluster and account for correlation between the explanatory variables, a logistic regression could be used. However, in our case, perfect separation – some independent variables

allowing to predict perfectly the appurtenance – precludes it (Allison, 2008). This is why we used instead a classification tree, computed with the R package "rpart" (Therneau, Atkinson & Ripley, 2017), to better understand which variables are the most responsible for the separation and to uncover at which thresholds separation occurs on these variables. Classification trees are a specific form of decision trees, when the target variable, i.e. the belonging to the cluster of the double performing farms, is a binary variable, as here. For each independent variable X, decision trees aim at partitioning the observations into two sets, $Z > Z_{break}$ and $Z' < Z_{break}$ so that the distance in the probability of belonging to the cluster of performing farms is minimized within each set and maximized between the two sets. The X which yields the most important separation is retained for the first partition and the procedure is repeated on each subset until a trade-off, fixed by the author, between the number of subsets and the number of observations in each subsets is reached.

4.3. Econometric analysis on the whole sample

After this descriptive analysis, we identify the practices which create synergies between the performances i.e. that influence in the same direction both performances. Conversely to O'Brien (2015) and Thomassen (2009), we do not use PLS regression because we do not find multicollinearity in our data when performing Variance Inflation Factor (VIF) calculation, using the R package "mctest" (Imdad & Aslam, 2018). No variable has a Variance Inflation Factor (VIF) larger than 5, which indicates that multicolinearity is not an issue. For further information, the correlations between the independent variables are summarized in the supplementary materials (SM 2).

We use four separate Ordinary Least Squares (OLS) regression models, with the environmental performance per liter, the economic performance per liter, the environmental performance per ha and the economic performance per ha as

dependent variables respectively. As independent variables, we use almost the same set of farms' characteristics and practices as the previous part of the analysis (Table 1). Only the yields of corn and cereals are not retained as they are not an agricultural practice, something the farmers can easily choose. We end up with 4 separate regression equations following the classical linear form:

$$Y = \beta X + \varepsilon$$

Where Y is a [118x1] matrix of either the environmental performance per liter, the economic performance per liter, the environmental performance per ha and the economic performance per ha observations for each farm, β is a [18x1] matrix of regression coefficients, different for each of the 4 models, X is a [118x18] matrix, similar for each equation (SM 1) and ε is a [118x1] matrix of error terms.

We then compare the 20 regression coefficients, which differ across the OLS models and identify the explanatory variables that affects in the same direction both the environmental and economic performances (synergies). To identify practices with not only a significant effect but also an important effect size, we calculate the effect size as the multiplication of the range between first and third quartile in X – to capture the actual variability in the sample – with the associated regression coefficient.

However, the errors terms of the equations 1 and 2 and of the equations 3 and 4 are correlated with one other when estimated by OLS regressions (respectively $\rho = 0.45$ and $\rho = -0.34$ respectively). These correlations indicate that at least one omitted variable is correlated with each couple of equation. Even if the 4 models seem superficially independent, they are in fact related by their correlated errors terms, which capture the influence of the omitted variables. Thus, jointly-estimating the models and using the information contains in the correlations of the errors terms, one can obtain a more precise estimator of the variance-covariance matrix of the errors terms. This Feasible Generalized Least Squares (FGLS) estimator is more efficient than the OLS estimator as more information is used to compute its estimated variance. Thus, the variance of the estimator is reduced

compare to the OLS procedure, and the confidence intervals for the estimated regression coefficients are smaller. To use this additional information, we replace the OLS estimation with a Seemingly Unrelated Regression (SUR) estimation.

Mathematically, the SUR models are composed of two equations each:

$$\text{Model 1} \quad \begin{cases} \text{Environmental Perf per L} = \beta_1 X + \varepsilon_1 \\ \text{Economic Perf per L} = \beta_2 X + \varepsilon_2 \end{cases}$$

$$\text{Model 2} \quad \begin{cases} \text{Environmental Perf per Ha} = \beta_3 X + \varepsilon_3 \\ \text{Economic Perf per Ha} = \beta_4 X + \varepsilon_4 \end{cases}$$

Where the errors terms are correlated:

$$E(\varepsilon) = 0$$

$$E(\varepsilon\varepsilon') = \begin{pmatrix} \sigma_{11} I_T & \sigma_{12} I_T & \cdots & \sigma_{1M} I_T \\ \sigma_{21} I_T & \sigma_{22} I_T & \cdots & \sigma_{2M} I_T \\ \vdots & \vdots & \cdots & \vdots \\ \sigma_{M1} I_T & \sigma_{M2} I_T & \cdots & \sigma_{MM} I_T \end{pmatrix} = \Sigma \otimes I_T = \psi$$

Then, the FGLS estimator of the regression coefficients is:

$$\begin{aligned} \hat{\beta} &= \left(X'\psi^{-1}X\right)^{-1} X'\psi^{-1}y \\ &= \left[X'\left(\Sigma^{-1} \otimes I_T\right)X\right]^{-1} X'\left(\Sigma^{-1} \otimes I_T\right)y \\ E\left(\hat{\beta}\right) &= \beta \\ V\left(\hat{\beta}\right) &= E\left(\hat{\beta} - \beta\right)\left(\hat{\beta} - \beta\right)' \\ &= \left(X'\psi^{-1}X\right)^{-1} \\ &= \left[X'\left(\Sigma^{-1} \otimes I_T\right)X\right]^{-1}. \end{aligned}$$

5. Results

5.1. A correctly reconstructed and relatively high economic performance of PDO farms

The average reconstructed revenue in our sample is 212 900€ and is not significantly different from the FADN inter-regional average (Welch t-test, p-value = 0.2512). The average total factor cost - 79 403€ -, and the average profit 133 497€, are not significantly different either. Note that the standard deviation of our two economic indicators, profit per liter and per hectare, is large: 34% and 57% respectively. This important variability is promising for statistical analysis.

The reconstituted revenue per L and total costs per L are close to the FADN's values, but our sample's variability is lower for the revenue per L and larger for the total costs per L (Figure 2 and Figure 3). The revenue per L is a bit higher in our sample, which is expected as PDO milk is sold at a higher price. Thus, the gross profit of the PDO farms is larger than the FADN's conventional farms. However, our reconstituted Profit per L has a higher variability (

Figure 4).

Figure 2. Comparison of the distribution of the reconstituted revenue per liter and the FADN's one

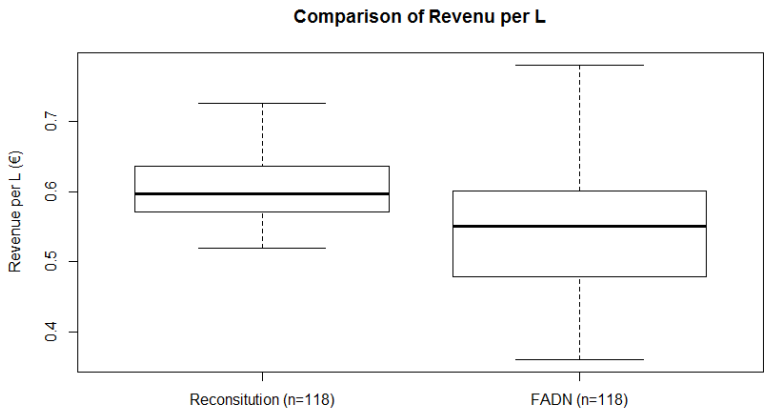


Figure 3: Comparison of the distribution of the reconstituted total costs per liter and the FADN's one

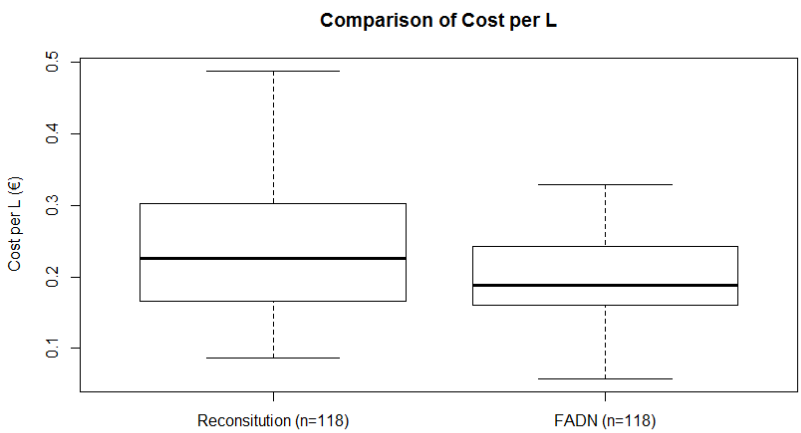
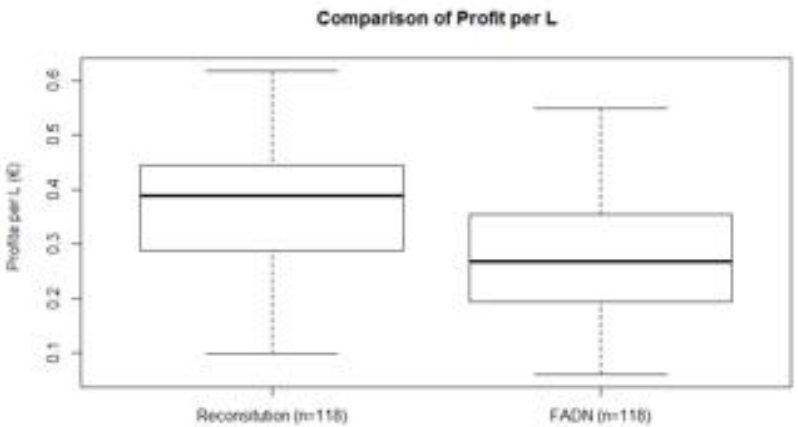


Figure 4: Comparison of the distribution of the reconstituted gross profit per L and the FADN's one



The indicators of environmental performance are the gross GHG emissions per liter and per hectare and are gathered in the CAP'2ER data, which averages respectively at 1.06 kg CO2eq per L (sd = 0.21 kg CO2eq) and 3134 kg CO2eq per ha (sd = 1 318 kg CO2eq).

5.2. Synergies and antagonisms between economic and environmental performances

At this state of the analysis, we can precise the relationships between the economic and environmental performances in our sample of PDO farms using a correlation matrix of their indicators (Figure 5).

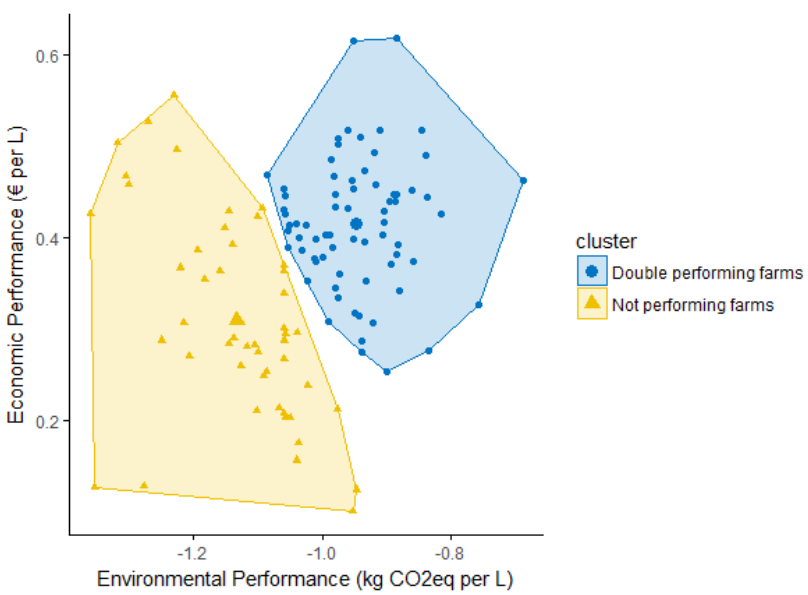
Figure 5. Correlation matrix of environmental and economic performances' indicators

Overall, environmental performance per liter (Figure 5) is synergetic (positively correlated) with the different profitability indicators (€ per L and per Ha) which indicates that the GHG emissions per L can be decreased while the profitability can be increased, i.e. that the PDO farms can be both environmentally and economically performant. Environmental performance per hectare however is globally antagonistic - negatively correlated – to economic performance per hectare, which indicates a trade off between environmental and economic performance when they are measured on a hectare basis. Thus, the choice of the indicators' measurement unit impacts the relationships between environmental and economic performances.

5.3. Two clusters of farms, one of which is double performing

The hierarchical clustering results in two cluster: one grouping the most environmentally and economically performant farms (double performance) and one grouping the least performant ones (Figure 6).

Figure 6. Clusters plot from the k-mean clustering



The associated dendrogram and Dindex values plots, which are used to define the optimal number of clusters as 2, are provided in the Supplementary Materials (SM 4). The two clusters are well-defined, with the cluster of the double performing farms being larger (n = 70) than the cluster of the not performing farms (n = 48). The double performing farms have a higher economic performance and lower GHG emissions (so higher environmental performance) than the not performing farms (Table 1).

In the cluster of double performing farms, the environmental performance per liter and the economic performance per liter are not correlated (Table 1). In the cluster of the not performing farms, there is a strong negative correlation between environmental performance per liter and economic performance per liter. In this case, a trade-off occurs between the environmental and economic performances.

Table 1. Clusters' characteristics

Mean values

Clusters	Environmental Performance per L	Economic Performance per L	Size	Correlation
Double performing farms	-0,95	0,40	70	0.03
Not performing farms	-1,13	0,30	48	-0.50

To gain further knowledge on the difference between the two clusters, and to identify some farms' characteristics or farming practices that differ between the clusters, we perform multiples t-tests between the double performing and the not performing farms' clusters. Obviously, the environmental and economic performances are significantly different between the two clusters (Table 2, $p < 0.0001$). More interestingly, double performing farms have a larger herd and their

cows have an earlier first calving (and thus start producing earlier). Moreover, double performing farm have a higher yield of fodder corn and cereals. They also have a larger share of their total area devoted to temporary pastures and they keep these temporary pastures longer before plowing them again. Lastly, performing farms use more organic fertilizers per ha than the not performing ones, which could explain their higher yields.

Table 2. Summary of the farms' characteristics per cluster

	Sample Average	Performing farms	Not Performing farms
Environmental Performance per L	-1.06 (0.28)	-0.93*** (0.237)	-1.21*** (0.239)
Economic Performance per L	0.35 (0.12)	0.40*** (0.073)	0.276*** (0.142)
Concentrate bought	1 094.9 (627.42)	78.96 (65.805)	69.68 (77.6)
Herd's size	-3 134.5 (1	103.95*** (51.38)	74.39*** (44.78)

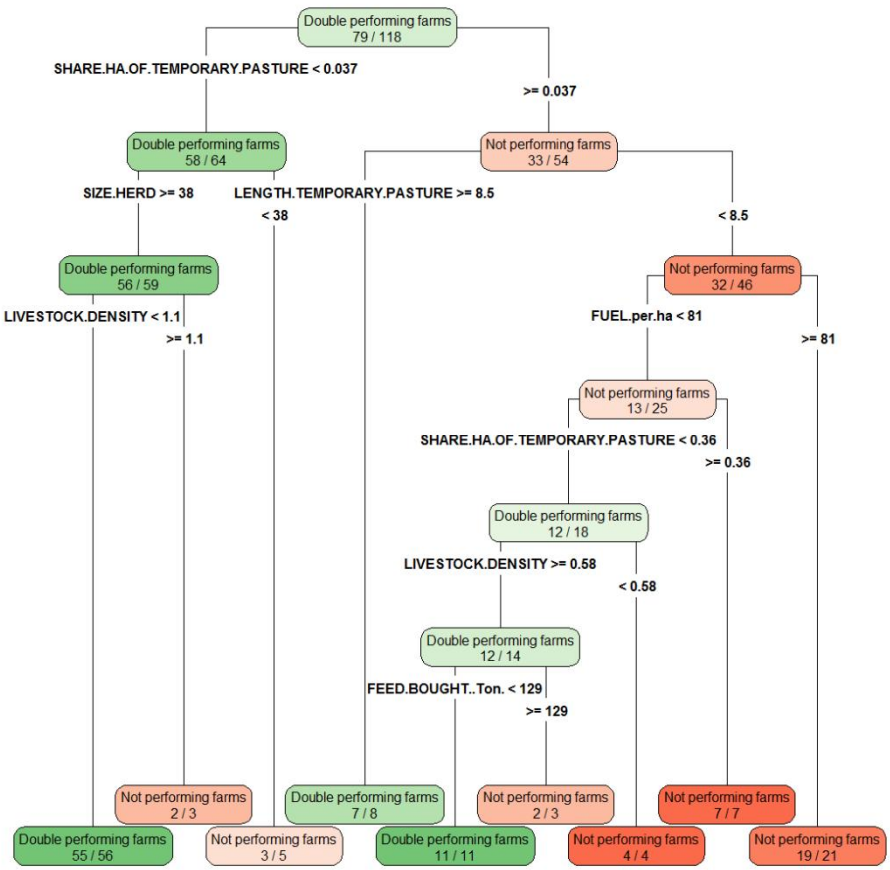
	318.76)		
Labor Use	1 094.9 (627.42)	1.81 (1.085)	1.895 (1.075)
Fuel per Ha	66.76 (35.85)	69.345 (29.48)	62.986 (43.57)
Electricity per cow	354.7 (171.46)	338.14 (160.13)	378.87 (185.82)
Share protein in the diet	0.14 (0.01)	0.139 (0.009)	0.14 (0.013)
Share of pasture	0.71 (0.26)	0.699 (0.257)	0.728 (0.264)
Age first calving	32.37 (3.06)	31.714*** (2.99)	33.33*** (2.94)
Biodiversity per Ha	3.38 (2.08)	3.565 (2.06)	3.108 (2.091)
Herd's Renewal Rate	2.55 (7.96)	1.966 (7.235)	3.398 (8.9283)
Share forage land	0.01 (0.02)	0.007 (0.017)	0.005 (0.015)
Yield of cereals	2.25 (2.86)	2.942*** (2.876)	1.243*** (2.538)
Yield of forage	2.17 (4.20)	2.813** (4.627)	1.228** (3.316)
Share temporary pasture	160.47 (55.77)	0.169*** (0.188)	0.051*** (0.0886)
Length temporary pasture	2.91	3.649*	1.831*

	(3.63)	(3.736)	(3.22)
Days spent on pasture	160.47 (55.77)	159.71 (57.612)	161.56 (53.55)
Livestock density	0.14 (0.01)	0.76 (0.173)	0.699 (0.297)
Mineral azote spread	15.35 (16.53)	15.94 (15.377)	14.498 (18.213)
Organic azote spread	29.52 (16.34)	32.297** (16.41)	25.326** (15.469)

*p**p***p<0.01

The data analysis is continued with a classification tree to understand which variables are the most responsible for the perfect separation between the two clusters (Result of the logistic regression, cf. Methodology part) and to know, for each variable, which specific value is separating the sample into the two clusters. The variable that explains most of the separation between the clusters is the share of temporary pasture, which is negatively correlated with the share of pasture (SM 2). If a farm has less than 3.7% of temporary pasture, then it is likely be double performing. Farms are also more likely to be double performing when each temporary pasture's rotation lasts more than 8.5 years. The performing farms use less than 81 L of fuel per ha per year and buy less than 129 Ton of concentrate and feed per year. The performing farms generally have a livestock density lower than 1.1 cows per ha.

Figure 7. Classification tree for the belonging to each farm cluster



Using such classification tree, the variables that are mainly responsible for the separation of the 118 farms between the two clusters are uncovered, as well as the thresholds at which a specific farm belong to the double performing cluster.

5.4. No driver of double performance but many "no regret" levers

Table 3. Results of the SUR model

Environmental performance	Economic performance	Environmental performance	Economic performance

	per L	per L	per Ha	per Ha
	(1)	(2)	(3)	(4)
Concentrate bought	-0.00	-0.00	-0.79	-0.82
	(0.00)	(0.00)	(0.76)	(0.76)
Herd's size	0.00	0.00***	2.27*	3.32***
	(0.00)	(0.00)	(0.96)	(0.95)
Labor use	-0.00	-0.06***	-26.02	-178.5***
	(0.02)	(0.01)	(37.62)	(37.29)
Fuel per Ha	-0.00	-0.00	-6.63***	1.50
	(0.00)	(0.00)	(1.46)	(1.45)
Electricity per cow	0.00	0.00	-0.97***	0.39
	(0.00)	(0.00)	(0.23)	(0.23)
Share protein in the diet	-5.63*	-0.07	-20,389.40***	864.56
	(2.40)	(0.90)	(3781.98)	(3748.4)
Share of pasture	-0.02	-0.06	149.36	-32.56
	(0.14)	(0.05)	(215.35)	(213.44)
Age first calving	-0.01	-0.00	14.20	-33.47*
	(0.01)	(0.00)	(14.92)	(14.79)
Biodiversity per Ha	0.05**	0.00	10.90	-15.47
	(0.01)	(0.01)	(22.87)	(22.67)
Herd's Renewal Rate	-0.00	-0.00**	-10.77*	-1.40
	(0.00)	(0.00)	(4.79)	(4.75)
Share forage land	0.40	0.36	-9329.99***	5220.62*
	(1.63)	(0.61)	(2576.20)	(2553.3)
Share temporary pasture	0.37	0.16	-2354.79	1105.7**
	(0.24)	(0.09)	(374.28)	(370.96)
Length temporary pasture	-0.01	-0.00	1.69	-8.39

	(0.01)	(0.00)	(15.10)	(14.96)
Days spent on pasture	0.00	-0.00	-0.23	-0.46
	(0.00)	(0.00)	(0.76)	(0.75)
Livestock density	0.34*	-0.04	-2758.16***	581.4*
	(0.16)	(0.06)	(246.36)	(244.17)
Mineral azote spread	0.00	-0.00	-16.45***	5.53
	(0.00)	(0.00)	(2.88)	(2.86)
Organic azote spread	-0.00	-0.00	-4.14	3.91
	(0.00)	(0.00)	(3.41)	(3.38)
Constant	-0.37	0.51**	2848.11***	1286.8
	(0.51)	(0.19)	(807.28)	(800.12)
Observations	118	118	118	118
R^2	0.35	0.54	0.94	0.69
Adjusted R^2	0.24	0.47	0.93	0.64
Residual Std. Error (df = 100)	0.24	0.09	378.2	374.93

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Model fit (adjusted r-square) ranges between 0.24 and 0.9, with a higher fit when performance is expressed on a per hectare basis (Table 3). The heteroscedasticity of the OLS models is corrected by the SUR procedure (p-value of Breusch-Pagan tests = 0.54; 0.98; 0.92; 0.99 respectively, see also SM 5). Several alternative specifications were attempted to test the robustness of the models such as adding external labor use as to the explanatory variables, allocating all GHG emissions to milk production instead of the default energy-based allocation to milk, meat and cereals in CAP2'ER or by restricting the perimeter of GHG emissions to the farms by ignoring emissions from the production and transportation of concentrates and fertilizers. We also tested WLS models which do not account for the correlation of the errors terms instead of the SUR models, giving biased estimators but yielding higher R^2 (SM 6). None of these alternative specifications triggered major changes in estimators or their significance (SM 7 to SM 9). As expected, the SUR models which yields smaller R^2 than the WLS mod

A single characteristic improves both environmental and economic performance, namely herd size (Figure 8), and only when performance is expressed on a per hectare basis. Therefore, synergies are scarce. So are trade-offs: only livestock density counts as one, again only when performance is expressed on a per hectare basis. Increasing livestock density increases economic performance at the expense of environmental performance. Many no regrets levers are however identified.

Figure 8. Synergies, levers and antagonisms in economic and environmental performance

	Indicators per L	Indicators per Ha
Synergy	None	Herd's Size ⇧
Lever on the Environmental Performance	Share protein in diet ⇩ Biodiversity per ha ⇧ Livestock density ⇧	Fuel per ha ⇩ *Electricity per cow* ⇩ Share protein in diet ⇩ *Ratio cow/heifer* ⇩ Mineral N per ha ⇩
Lever on the Economic Performance	Labor use ⇩ Herd's size ⇧ *Ratio cow/heifer* ⇩	Labor use ⇩ Age first calf ⇩ Share acreage of temporary pasture ⇧
Trade-off	None	*Share acreage corn* ⇩ ⇧ Livestock density ⇩ ⇧

In italic are the variables that have weak effect sizes.

Figure 9. Effect sizes of practices on environmental performance per liter

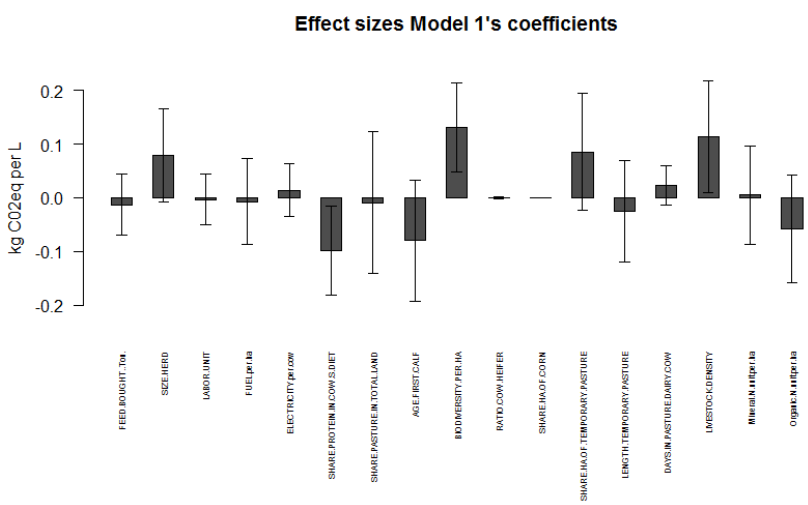


Figure 10. Effect sizes of practices on economic performance per liter

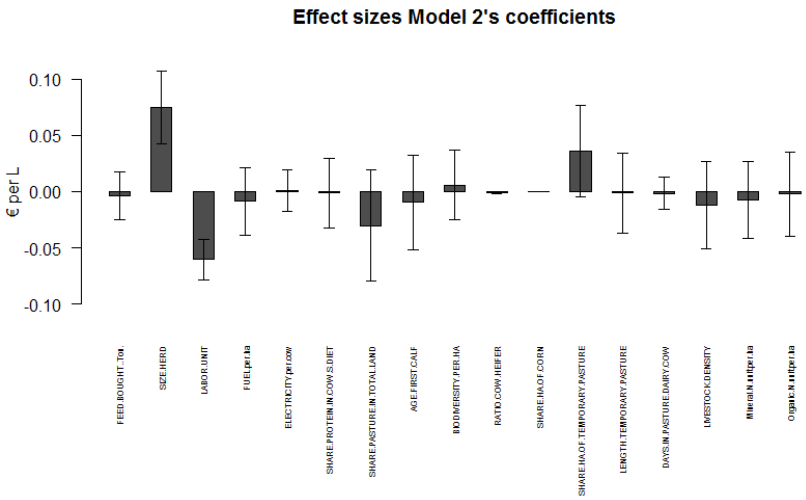


Figure 11. Effect sizes of practices on environmental performance per hectare

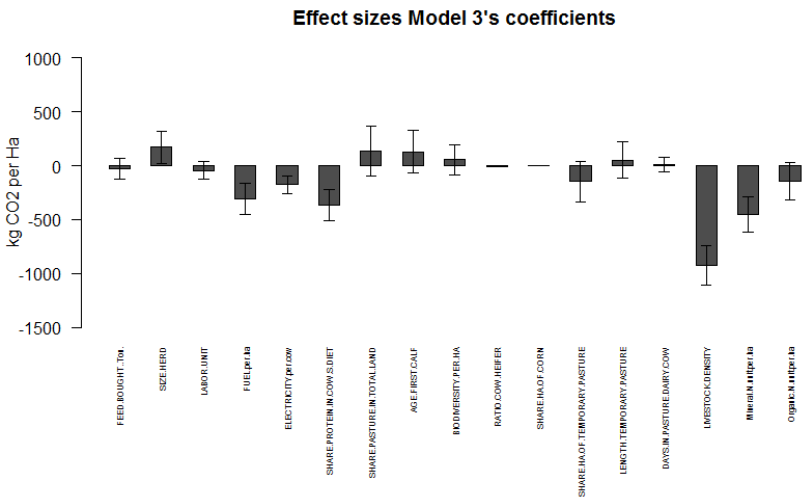
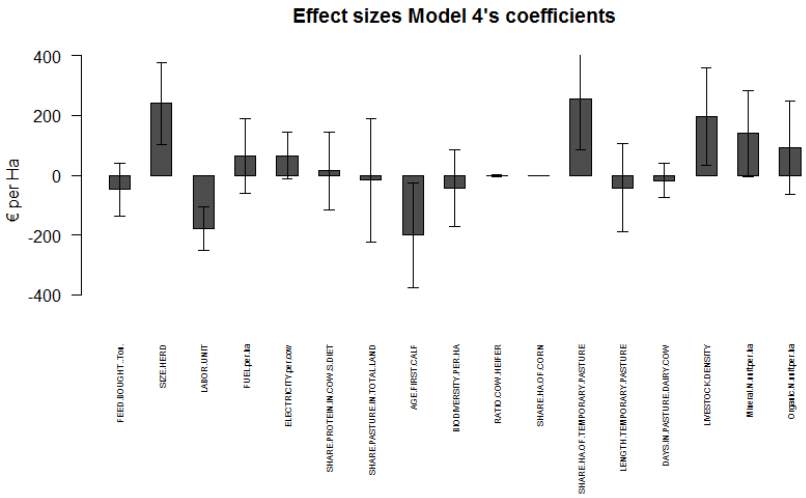


Figure 12. Effect sizes of practices on economic performance per hectare



Levers on the environmental performance per liter

The share of protein in the cows' diet has a negative influence on the environmental performance per liter, with a strong effect size (Figure 9). Decreasing the share of protein in the cows' diet by 1 percentage point (pp) result in a gain of environmental performance per liter of 3.4%.

The livestock density and the biodiversity per ha have a positive impact of the environmental performance per liter, both with strong effect sizes (

Figure 10).

Levers on the economic performance per liter

The herd's size has a positive impact on the economic performance per L and a very strong effect size (

Figure 10. Effect sizes

Figure 10). Conversely, the labor use and the ration of cows over heifers have a negative impact on the environmental performance per L but only the former has a significant effect size.

Levers on the environmental performance per hectare

The share of protein in the cows' diet, the fuel consumption per ha, the electricity consumed per cow in kWh, the ratio between producing cows and heifers, and the amount of mineral fertilizers spread per ha in N unit all have a negative influence on the environmental performance per ha. Among them, only the mineral fertilizers spread per ha, the fuel per ha and the share of protein in the cows' diet, have strong effect sizes (Figure 11).

Levers on the economic performance per hectare

The share of temporary pasture in the total acreage has a significant positive impact on the economic performance per ha with a strong effect size (Figure 12)

The age of the heifers when they have their first calf and the labor use significantly decrease the economic performance per ha, both with important effect sizes.

6. Discussion

6.1. Interpretation of the characteristics of double performant farms

Our first goal in this paper is to classify the PDO farms into a performant and a non-performant groups and to understand which farms' characteristics or practices differ between the two clusters. By doing so, we can uncover some key practices and thresholds a farm could follow to improve its environmental and economic performances.

In our sample, a typical performant farm has a high renewal rate and its cows have an early first calving, which reduce the deadweight of the non-productive heifers. The cows also graze for a longer time, which reduces the amount of feed and concentrate bought by the farm and increases its profitability. The cows also graze for a longer time, which reduces the amount of feed and concentrate bought by the farm and increases its profitability. The double performing farms use less mineral fertilizers and more organic ones. This substitution improves both farm profitability – manure being largely costless – and carbon performance: while the nature of nitrogen inputs does not strongly impact field emissions, mineral fertilizers bear an additional carbon burden coming from their production process. The performant farms also use relatively more temporary pastures and keep them longer before ploughing them again, which reduces the use of tractors (less fuel consumption per ha) and increases the share of grass in cows' diet (SM 2). Moreover, the share of temporary pasture is positively correlated with the yield of corn and cereals, which could indicate that temporary pasture, because they stock nutrients in the soil, are more fertile than usual agricultural soil, and that when these pastures are used later for cropping, the crops' yields are increased.

Conversely, the performant farms have relatively less permanent pastures, even if their cows spend more time on them, which could indicates that using more

long duration temporary pasture is more environmentally and economically performant than permanent pasture, as the former is more productive than the latter (Smit, Metzger, & Ewert, 2008). Nevertheless, the carbon sequestration is not accounted for in our analysis, and permanent pasture are known to be larger carbon sink than temporary ones (Leifeld, Bassin, & Fuhrer, 2005).

6.2. Correlation between environmental and economic performance

In our sample, environmental and economic performances are moderately positively correlated ($\rho = 0.28$) when measured per liter, and strongly negatively correlated when measured per hectare ($\rho = - 0.68$). This could be explained by a dominant effect of productivity per hectare which increases both per liter performances but likely increases as well emissions per hectare.

O'Brien et al. (2015), who only use per liter indicators, also find a positive correlation between the environmental and economic performances in their sample ($\rho = 0.43$). However, Thomassen et al. (2009) extract a negative correlation between the environmental and economic performances per liter ($\rho = -0.31$). In a word, the Irish paper, which also studies extensive dairy farming, also find a synergy between both performance per liter, while the Dutch paper, which analyses intensive dairy farming, estimates a trade-off between both performances. Compare to our results, it can be assumed that extensive faming leads to a synergy between the performances, because these farms use less polluting inputs (mineral fertilizers, fuel or electricity) and thus have both less GHG emissions and variable costs.

6.3. Diverging results on the effects of farms' characteristics and practices on the performances

As we aim at understanding better the relationships between environmental and economic performance and the above-mentioned contradicting results between the extensive and intensive farming's cases, we will discuss in detail these points.

In the case of extensive Irish farms, the length of the grazing season is the most important levers on both the environmental and economic performances (synergy). The conclusions drawn are that an extensive livestock farming, limiting the use of concentrate feed (which has a negative influence on both performances in their study) and depending more on pasture and meadows can outperform more intensive farms, mainly because more pasture means more carbon sequestration in soils. But one can wonder if extensive farming is also more environmentally performant when carbon sequestration is not taken into account, a question we answer positively. Moreover, because both the length of the grazing season and the yield of milk per ha or per cow are negatively correlated with the GHG emissions of milk, O'Brien et al. (2015) shows that extensive diets could also result in a high milk productivity and that by reducing the feed costs, extensive grazing can reduce the farms' total and variable costs and thus extend their profitability.

To the contrary, in the case of intensive Dutch farms, Thomassen et al. (2009) shows that a high share of concentrate feed in cows' diet results in lower GHG emissions per liter of milk thanks to higher milk productivity and lower emissions per unit of feed (Lovett, Shalloo, Dillon, & O'Mara, 2006). However, gross profit per liter is reduced because of the feed costs. So, as the high milk productivity is due to a concentrate-rich diet, and because it implies a high environmental performance (low GHG emissions) and a low gross profit, both are positively correlated, which indicate that environment performance cannot be enhanced without decreasing farms' profitability.

In a nutshell, the debate is centered on the role of concentrate feed in the environmental and economic performance. Here we confirm a negative role of

excessive concentrate feed. Thomassen's results may be explained by a high level of dependence on concentrate, which can be an effective way to reduce GHG emission by lowering enteric fermentation (Lovett, Shalloo, Dillon, & O'Mara, 2008) and to increase profitability by rising the cows' productivity (Thomassen et al., 2009). But, as our study and the Irish case demonstrate, increasing the grazing season and using highly productive pastures can also create a synergy between environmental and economic performance as increasing the grazed grass in the cows' diet can improve the digestibility of the forage and thus reduce the enteric fermentation and the CH4 emission (Dillon, Crosse, O'Brien, & Mayes, 2002). Moreover, (Kiefer et al., 2014) compare organic and conventional farming in Germany and also find that reducing concentrates use limits the GHG emissions and increase the profitability.

In addition O'Brien et al (2015) find that the economic performant farms use more feed and concentrate in the cows' diet compared to not performing farms. As the main difference between the Irish case and ours is the PDO labelling, it seems that PDO dairy farming, because it limits the capacity of the farmers to buy fodder crops and feed from the exterior, forces them to develop other feeding alternatives, such as high productive temporary pasture. Thus, coupled with an efficient fertilizers' use, PDO performant farms can have a relatively high livestock density while not depending on feed and concentrate imports.

In this debate, the originality of our study is to propose another statistical approach to this question and to study the performances per liter and per hectare. More precisely, we find that the amount of concentrate and feed bought does not have a significant influence on the performances, when measured either per L or per Ha. Nevertheless, the share of protein in the cows' diet, which is closely related to the feed and concentrates use as the latter is protein-rich compared to grazed grass, is decreasing the environmental performance per ha. However, we could not find a significant relationship between the share of protein in the cows' diet and the economic performance, per L or per Ha. Thus, reducing this farming practice could

reduce GHG emissions while keeping profit at the same level, which contradicts O'Brien et al. (2015)'s findings on extensive dairy farming's performances.

6.4. Methodological advantages of the study

One of the benefits of our SUR model compared to the PLS regressions used by O'Brien et al. (2015) and Thomassen et al. (2009) is the number of levers that come out. As the PLS identify levers through the latent variables, this methodology only identifies 3 or 4 variables. Thus, we uncover 7 variables that can act as levers towards sustainability on one or both performances per liter and 10 variables for the performances per ha (Figure 8).

Also, using two indicators for the performances, per L and per Ha, is helpful to limit interpretation bias. Indeed, reasoning with product-based indicators only hold the risk of underestimating the environmental impact of intensive practices. As the per liter measure of the environmental performance is the ratio between the GHG emissions and the milk production, if a practice increases the cows' productivity more that it increases the GHG emissions, it will increase the environmental performance per liter. However, this practice would increase the GHG emissions, measure for the farm, per cow or per hectare. For example, in our study, we do not find many practices that impact both performance. Only decreasing the share protein in the cows' diet or the labor use are identified as levers in both SUR models. The other identified levers are less robust and the recommendations to the farmers thus depend on the choice of the indicator.

6.5. Limits of the study

An important limit of our study is related to the computation of the GHG emission. The LCA data we use does not take into account GHG emissions from the P2O5 and K2O fertilizers' production and transportation. Moreover, when the

transportation of the other fertilizers or concentrates is accounted for, a standardized value is used, as not precise information is gathered on the production sites of such fertilizers or concentrates. The gross GHG emission's estimation are thus not complete nor perfect. Moreover, we use the gross GHG emission and do not account for the carbon sequestration in the permanent and temporary pastures. One may consider that including carbon sequestration could change our classification of the double performing and the not performing ones as the most extensive farms in our same would have a high carbon sequestration. As a higher carbon sequestration means lower net GHG emissions, the extensive farms would be relatively more environmentally performant. Nevertheless, O'Brien et al. (2015) show that including carbon sequestration and thus studying on net GHG emissions does not modify the relationships between the environmental and economic performances. The LCA analysis in CAP2'ER does not take into account the carbon sequestration of the land used to produce the concentrate and feed bought by the farms.

Other limits are related to the econometric model. Important omitted variables are likely to have been omitted, at least in the models with low adjusted r-square. These omitted variables, such as farmer dynamism or competence, or pedo-climatic conditions, could be correlated with both the dependent variables and practices, biasing the estimators (endogeneity). We believe that this risk is limited by the homogeneity of our sample (same region, all PDO farms included in the same farmer association …). However, we cannot rule it out and the causality of the relationship we point out must be carefully pondered. Another limit rises from the fact the SUR model does not estimate the relationships between the dependent variables. Some extra information could be gathered by regressing the economic performance and the other independent variables on the environmental performance and vice versa. This econometric model would be related to a Simultaneous Equations model, which could be developed in a further study.

Also, the survey from which we obtained the analyzed data were voluntary, so only willingful farmers were sampled. It might be possible that a selection bias

exists in our sample, if the sampled farmers were on average more informed about GHG emissions, more connected with academic research or already the most performant of the study area.

7. Conclusion

In this paper, we identify which characteristics or practices differentiate the performing farms from the non-performing farms. The former generally have a higher renewal rate, a larger herd, they use less inputs (feed, concentrate, mineral fertilizers and fuel), their cows have their first calf younger, they spend more time in pastures and the acreage of temporary pastures as well as their lengths are higher. Even if they use less mineral fertilizers, the performing farms spread more manure on their fields and have higher yields, which indicates that more environmental friendly practices can also improve the farms' profitability.

Our regression model questions the possibility of synergies between economic and environmental performance, but also the existence of necessary trade-offs. We identify however multiple no-regret levers: increasing livestock density, biodiversity or reducing the share of protein in the cows' diet improve the environmental performance per L without impacting economic performance. Conversely, decreasing the labor use or increasing farm size enhance economic performance per L without increasing emissions.

When measured on a per hectare basis, environmental gains can be reached without impacting profits by reducing the share of protein in cows' diet, fuel use per ha and mineral fertilizers. Conversely, reducing the age of first calving and labor use or increasing the share of temporary pasture improves economic performance without increasing emissions.

To fully study the environmental and economic performances of PDO dairy farming, we develop a methodology based on cluster analysis, classification tree and multiples regression. By doing so, we provide new information on the sustainability of specific practices (increasing the grazing season or reducing the age of the cows when they have their first calf) and a complete methodology that could be used in further studies on environmental and economic performances.

Precisely, we hope some research will be done comparing the performances of PDO and conventional farming in the same country, or comparing PDO farming across production situations. Our methodology could also be improved with the addition of a robust estimation of carbon sequestration, which would permit to use net GHG emissions as an environmental performance's indicator.

Limits of this paper come from the study region and the sample selection. Indeed, we study the performances of the PDO farms among the same region and using only PDO farms in our statistical population. This can be beneficial as we can compare farms that share a similar production situation, but limits the validity of any comparison with conventional dairy farming or PDO farming in other areas. Thus, the research on PDO farming and sustainable practices in agriculture could be improved by an analysis that would compare PDO farming in two different countries or production situations. Reproducing our analysis for the conventional dairy sector in France and comparing the results with ours could help defining if PDO dairy farming is more economically and environmentally performant, so more sustainable, that the conventional one.

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Supplementary Materials

SM 1. Descriptive Statistics of the farms' characteristics and farming practices.

		N	Mean	Min	Max
Environmental Performance per L	Environmental Performance per liter, in kg CO2eq (opposite of GHG emissions per liter).[1,3]	118	-1.06 (0.28)	-2.29	0.84
Economic Performance per L	Economic Performance per liter, in € (gross profit per liter).[2]	118	0.35 (0.12)	-0.14	0.62
Economic Performance per Ha	Economic Performance per hectare, in € (Gross profit per ha).[2]	118	1 094.9 (627.42)	-570.95	3 259.80
Environmental Performance per Ha	Environmental Performance per hectare, in kg CO2eq (opposite of GHG emissions per ha).[1]	118	-3 134.5 (1 318.76)	-6 861.80	-762.7
Concentrate bought	Ton of concentrate feed bought per year in tons.[1]	118	75.19 (70.67)	0.1	415.46
Herd's size	Number of cows in the herd. Heifers are accounted as 0.5.[1]	118	91.93	18.61	249

			(50.75)		
Labor Use	Number of persons working on the farm, owner included. [1]	118	1.85 (1.08)	1	6.3
Fuel per Ha	Fuel consumption per hectare per year in liter.[1]	118	66.76 (35.85)	9.91	185.24
Electricity per cow	Electricity consumption per cow per year in Kwh.[1]	118	354.7 (171.46)	62.5	1030.1
Share protein in the diet	Share of protein matter in cows' diet in percentage.[1]	118	0.14 (0.01)	0.12	0.19
Share of pasture	Share of pasture area in total acreage of the farm, %.[1]	118	0.71 (0.26)	0.13	1
Age first calving	Age of the cows when they give birth to their first calf and start producing milk, in months.[1]	118	32.37 (3.06)	26	39
Biodiversity per Ha	Biodiversity per hectare, computed following the ministry guidelines (Ministère de l'Agriculture et de l'Alimentation, 2015b).[1,4]	118	3.38 (2.08)	0.19	10.17
Herd's Renewal Rate	Ration of the number of cows on the number of heifer, proxy for the	118		0.52	61

	renewal rate of the herd.[1]		2.55 (7.96)		
Share forage land	Share of forage land area in total acreage of the farm, %.[1]	118	0.01 (0.02)	0	0.09
Yield of cereals	Yield of the cereals fields, ton per hectare. Source:[1]	118	2.25 (2.86)	0	7.9
Yield of forage	Yield of the fodder corn fields, ton per hectare.[1]	118	2.17 (4.20)	0	13
Share temporary pasture	Share of temporary pasture area in total acreage of the farm.[1]	118	0.12 (0.17)	0	0.71
Length temporary pasture	Average length of the temporary pastures, in year.[1]	118	2.91 (3.63)	0	16.35
Days spent on pasture	Numbers of days per year spent by the cows on pastures (temporary pastures included).[1]	118	160.47 (55.77)	0	245
Livestock density	Livestock density as the ration between the number of cows and the acreage of pasture land.[1]	118	0.74 (0.23)	0.22	1.41

Mineral azote spread	Amount of mineral fertilizers (azote, urea, potash and phosphate) spread per ha and per year, in N unit.[1]	118	15.35 (16.53)	0	77.78
Organic azote spread	Amount of organic fertilizers (manure) spread per ha and per year, in N unit.[1]	118	29.52 (16.34)	0	97.08

Sources: 1. Institut de L'Elevage, 2013; Michaud, 2016; Perrard, 2016.

2. FADN; Ministère de l'Agriculture et de l'Alimentation, 2015a, 2017; Eurostat, 2017.

3. The GHG emissions are computed using a Life Cycle Assessment, where all the GHG emitted for the milk production are used, from the cradle to the gate, including the production and transportation of all input produced off-farm (fertilizers, concentrated).

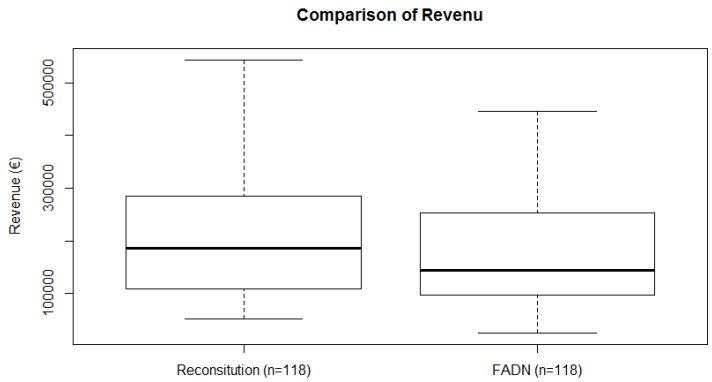
4. The biodiversity indicator is computed by aggregating all natural elements creating biodiversity (trees, hedge, terraces, and ponds) after applying a biodiversity coefficient to each type. For example, 1 linear meter of hedge corresponds to 10m² of biodiversity, while 1m² of pond correspond to 1m² of biodiversity.

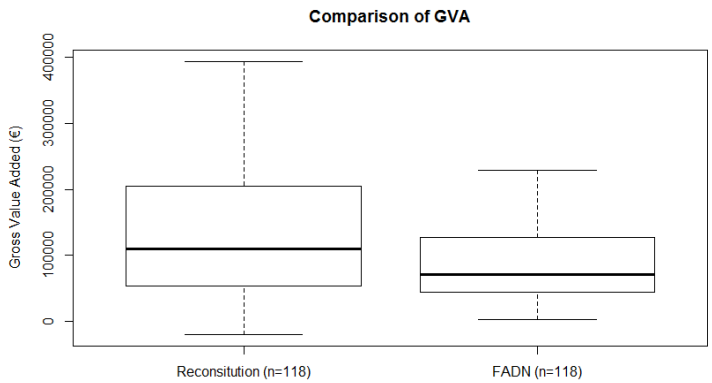
SM 2. Multicollinearity Check of the independent variables

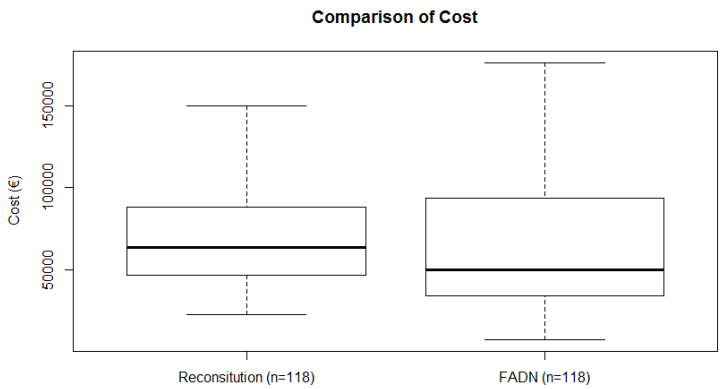
Variation Inflation Factors of the explanatory variables of the regression models

Variable	***VIF score***
FEED.BOUGHT.Ton.	2.38
SIZE.HERD	1.93
LABOR.UNIT	1.34
FUEL.per.ha	2.25
ELECTRICITY.per.cow	1.27
SHARE.PROTEIN.IN.COW.S.DIET	1.34
SHARE.PASTURE.IN.TOTAL.LAND	2.54
AGE.FIRST.CALF	1.71
BIODIVERSITY.PER.HA	1.84
RATIO.COW.HEIFER	1.19
SHARE.HA.OF.CORN	1.47
SHARE.HA.OF.TEMPORARY.PASTURE	3.13
LENGTH.TEMPORARY.PASTURE	2.46
DAYS.IN.PASTURE.DAIRY.COW	1.47
LIVESTOCK.DENSITY	2.68
Mineral.N.unit.per.ha	1.86
Organic.N.unit.per.ha	2.55

SM 3. Economic performance reconstitution

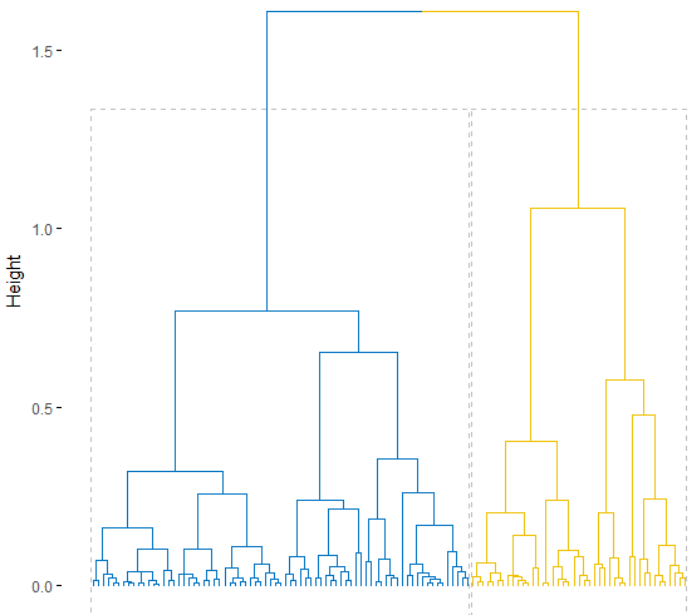




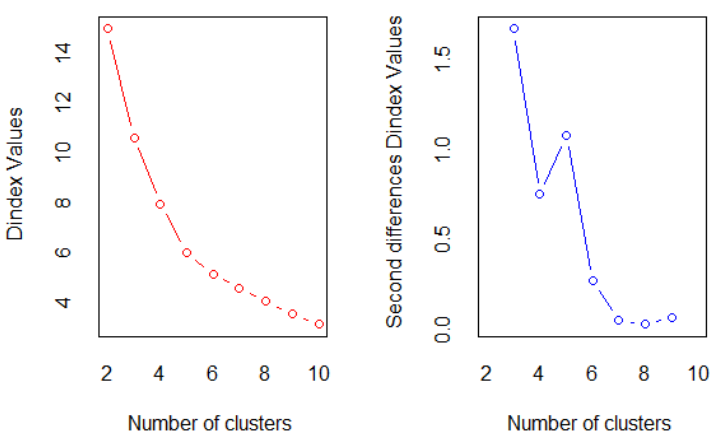


SM 4. Hierarchical clustering: optimal number of clusters

Dendogram of the hierarchical clustering



Dindex values plots



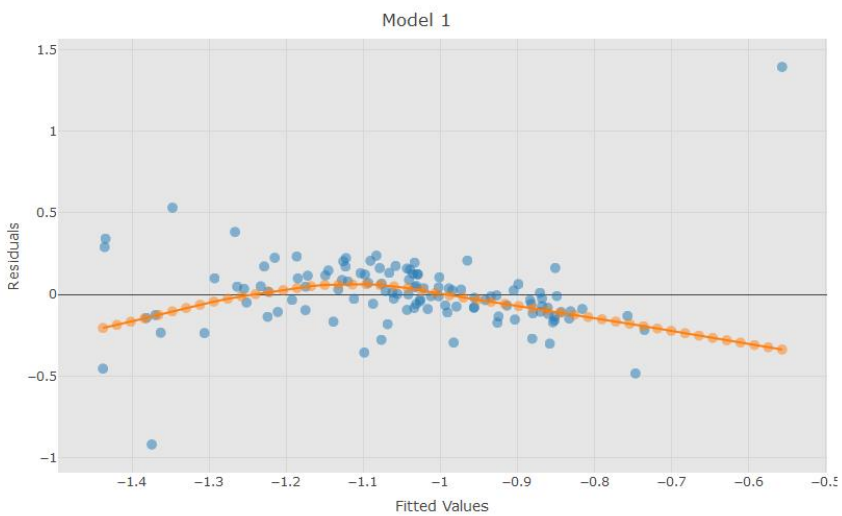
SM 5. Heteroscedasticity's correction Check of the SUR model

Breusch-Pagan tests

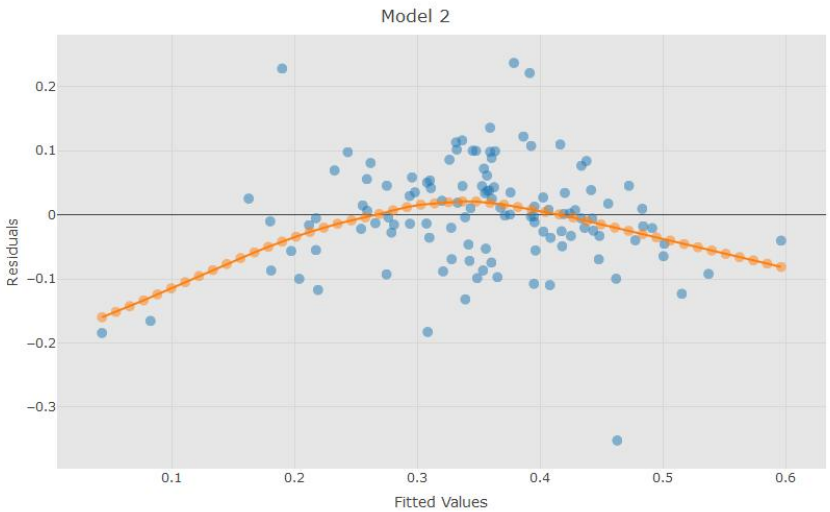
	Model (1)	Model (2)	Model (3)	Model (4)
Test statistic	16.93	30.43	25.47	35.44
Parameter	df = 17	df = 17	df = 17	df = 17
P.value	0.54	0.98	0.92	0.99

Note: $^{*}p^{**}p^{***}p<0.01$

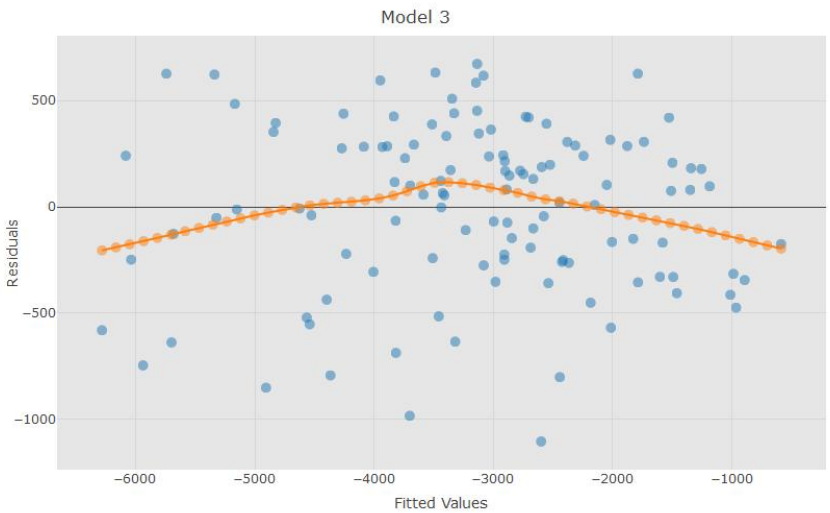
Residuals' plot for Model (1)



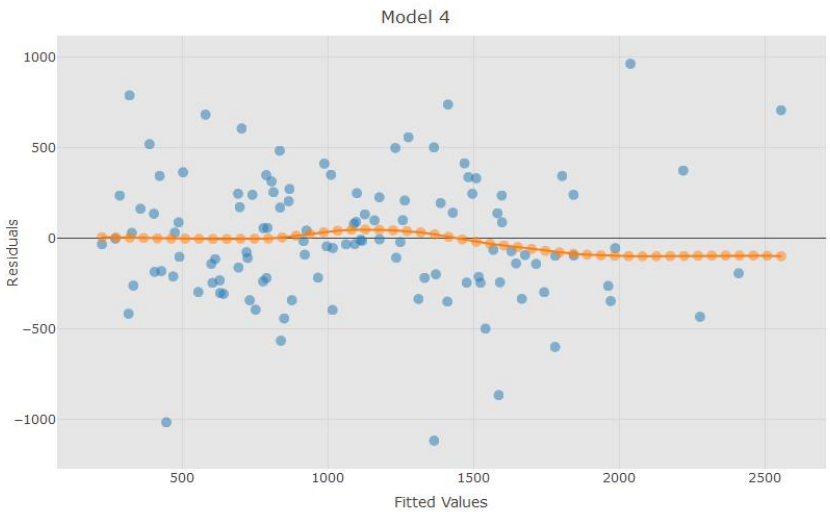
Residuals' plot for Model (2)



Residuals' plot for Model (3)



Residuals' plot for Model (4)



SM 6. Cross-validation of the SUR model

WLS regression models' output

	Dependent variable:			
	Environmental performance per L	Economic performance per L	Environmental performance per Ha	Economic Performance per Ha
	(1)	(2)	(3)	(4)
Concentrate bought	-0.0003*	-0.0004**	-1.061*	-1.018
	(0.0001)	(0.0002)	(0.536)	(0.790)
Herd's size	0.001**	0.001***	1.552**	4.238***
	(0.0003)	(0.0002)	(0.695)	(0.952)
Labor use	0.002	-0.049***	-49.11*	-166.01***
	(0.010)	(0.007)	(25.205)	(29.660)
Fuel per Ha	-0.0003	-0.0004*	-7.389***	2.115*
	(0.0004)	(0.0002)	(1.304)	(1.234)
Electricity per cow	0.0001*	0.00005	-0.588**	0.329
	(0.0001)	(0.00004)	(0.244)	(0.212)
Share protein in the diet	-3.324**	-0.353	-15065.1***	-16.431
	(1.330)	(0.623)	(3499.1)	(2610.04)
Share of pasture	0.170**	-0.032	-7.105	122.388
	(0.085)	(0.044)	(195.797)	(157.360)
Age first calving	-0.004	-0.003	13.571	-21.434*
	(0.005)	(0.002)	(12.441)	(11.911)
Biodiversity per Ha	0.023***	-0.002	22.986	-8.337
	(0.008)	(0.004)	(16.560)	(17.505)
Herd's Renewal Rate	-0.011*	-0.002	-15.875**	3.267

	(0.006)	(0.004)	(7.457)	(9.249)
Share forage land	0.516	0.301	-9586.7***	4624.84*
	(0.657)	(0.399)	(2566.34)	(2739.4)
Share temporary pasture	0.445***	0.117	-864.56***	1281.***
	(0.119)	(0.073)	(303.78)	(336.45)
Length temporary pasture	0.002	-0.001	6.211	-11.725
	(0.004)	(0.002)	(12.858)	(10.98)
Days spent on pasture	0.0002	-0.0002*	0.378	-0.393
	(0.0002)	(0.0001)	(0.671)	(0.580)
Livestock density	0.111	-0.084**	-2486.3***	456.02**
	(0.089)	(0.039)	(250.828)	(211.580)
Mineral azote spread	-0.0002	-0.00003	-17.87***	4.597*
	(0.001)	(0.0004)	(2.437)	(2.365)
Organic azote spread	-0.001	0.0001	-4.335	3.614
	(0.001)	(0.0005)	(2.999)	(2.576)
Constant	-0.853***	0.642***	1618.92**	843.4
	(0.272)	(0.126)	(744.966)	(645.48)
Observations	118	118	118	118
R^2	0.546	0.659	0.938	0.740
Adjusted R^2	0.469	0.601	0.928	0.696
Residual Std. Error (df = 100)	1.760	2.078	1.552	1.801
F Statistic (df = 17; 100)	7.077***	11.352***	89.100***	16.784***

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

SM 7. Sensibility Analysis: GHG emissions without allocation to milk

SUR regression output without allocation to milk

	Dependent variable:			
	Environmental performance per L	Economic performance per L	Environmental performance per Ha	Economic performance per Ha
	(1)	(2)	(3)	(4)
Concentrate bought	0.00	-0.00	-1.90*	-0.28
	(0.00)	(0.00)	(0.84)	(0.61)
Herd's size	0.00	0.00***	2.46*	3.07***
	(0.00)	(0.00)	(1.06)	(0.77)
Labor use	-0.00	-0.06***	10.32	-178.53***
	(0.03)	(0.01)	(41.54)	(30.18)
Fuel per Ha	0.00	-0.00	-4.24*	0.69
	(0.00)	(0.00)	(1.62)	(1.18)
Electricity per cow	0.00	0.00	-0.72**	0.27
	(0.00)	(0.00)	(0.25)	(0.18)
Share protein in the diet	-5.58	-0.07	-26585.8***	1054.8
	(3.17)	(0.90)	(4175.97)	(3033.8)
Share of pasture	0.09	-0.06	91.47	-5.72
	(0.18)	(0.05)	(237.79)	(172.75)
Age first calving	-0.00	-0.00	2.33	-22.09
	(0.01)	(0.00)	(16.47)	(11.97)
Biodiversity per Ha	0.03	0.00	-5.94	-6.43
	(0.02)	(0.01)	(25.26)	(18.35)

Herd's Renewal Rate	0.01	-0.00**	-4.47	-0.78
	(0.00)	(0.00)	(5.29)	(3.84)
Share forage land	0.07	0.36	663.18	1437.03
	(2.16)	(0.61)	(2844.57)	(2066.57)
Share temporary pasture	0.55	0.16	111.80	695.34*
	(0.31)	(0.09)	(413.27)	(300.24)
Length temporary pasture	-0.00	-0.00	-3.85	-4.02
	(0.01)	(0.00)	(16.67)	(12.11)
Days spent on pasture	0.00	-0.00	1.10	-0.51
	(0.00)	(0.00)	(0.84)	(0.61)
Livestock density	0.35	-0.04	-4655.5***	854.25***
	(0.21)	(0.06)	(272.02)	(197.62)
Mineral azote spread	0.00	-0.00	-16.86***	3.99
	(0.00)	(0.00)	(3.18)	(2.31)
Organic azote spread	0.00	-0.00	-9.44*	3.74
	(0.00)	(0.00)	(3.77)	(2.74)
Constant	-1.43*	0.51**	3633.8***	753.97
	(0.68)	(0.19)	(891.38)	(647.59)
Observations	118	118	118	118
R^2	0.26	0.54	0.94	0.72
Adjusted R^2	0.14	0.47	0.93	0.67
Residual Std. Error (df = 100)	0.317	0.09	417.6	303.45

Note: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

SM 8. Sensitivity Analysis: Adding external labor as explanatory variable

SUR regression output with external labor use

	Dependent variable:			
	Environmental performance per L	Economic performance per L	Environmental performance per Ha	Economic performance per Ha
	(1)	(2)	(3)	(4)
Concentrate bought	-0.00	-0.00	-0.54	-0.77
	(0.00)	(0.00)	(0.85)	(0.76)
Herd's size	0.00	0.00***	2.45*	3.19**
	(0.00)	(0.00)	(1.07)	(0.95)
Labor use	-0.00	-0.06***	-41.95	-181.8***
	(0.02)	(0.01)	(41.94)	(37.21)
Fuel per Ha	-0.00	-0.00	-7.04***	1.43
	(0.00)	(0.00)	(1.63)	(1.45)
Electricity per cow	0.00	0.00	-1.04***	0.39
	(0.00)	(0.00)	(0.26)	(0.23)
Share protein in the diet	-5.75*	-0.19	-20742.8***	434.66
	(2.42)	(0.90)	(4222.5)	(3746.5)
Share of pasture	-0.03	-0.07	299.28	-66.87
	(0.14)	(0.05)	(241.27)	(214.07)
Age first calving	-0.01	-0.00	20.59	-32.31*
	(0.01)	(0.00)	(16.63)	(14.75)
Biodiversity per Ha	0.05**	0.00	18.26	-14.81
	(0.01)	(0.01)	(25.45)	(22.58)
Herd's Renewal Rate	-0.00	-0.00*	-14.75**	-0.98

	(0.00)	(0.00)	(5.34)	(4.74)
Share forage land	0.23	0.20	-7550.03*	4633.55
	(1.66)	(0.62)	(2907.35)	(2579.6)
Share temporary Pasture	0.35	0.13	-586.73	1022.3**
	(0.24)	(0.09)	(422.12)	(374.53)
Length temporary pasture	-0.01	-0.00	11.83	-10.73
	(0.01)	(0.00)	(16.91)	(15.00)
Days spent on pasture	0.00	-0.00	0.22	-0.38
	(0.00)	(0.00)	(0.85)	(0.75)
Livestock density	0.34*	-0.03	-2764.6***	602.51*
	(0.16)	(0.06)	(274.62)	(243.67)
Mineral azote spread	0.00	-0.00	-18.15***	5.80*
	(0.00)	(0.00)	(3.22)	(2.85)
Organic azote spread	-0.00	0.00	-6.88	4.90
	(0.00)	(0.00)	(3.89)	(3.45)
External Labor	0.00	0.00	-0.64	1.03
	(0.00)	(0.00)	(0.86)	(0.76)
Constant	-0.38	0.51**	2184.7*	1276.27
	(0.51)	(0.19)	(898.11)	(796.86)
Observations	118	118	118	118
R^2	0.35	0.55	0.91	0.70
Adjusted R^2	0.24	0.47	0.90	0.65
Residual Std. Error (df = 100)	0.24	0.09	420.83	373.39

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

SM 9. Sensitivity Analysis: Changing the LCA's perimeter

SUR regression output without accounting for GHG emission from the production and transportation off-farm

	Dependent variable:			
	Environmental performance per L	Economic performance per L	Environmental performance per Ha	Economic performance per ha
	(1)	(2)	(3)	(4)
Concentrate bought	0.00	-0.00	-0.87	-0.82
	(0.00)	(0.00)	(0.46)	(0.76)
Herd's size	0.00	0.00***	0.96	3.32***
	(0.00)	(0.00)	(0.57)	(0.95)
Labor use	0.00	-0.06***	-2.65	-178.54***
	(0.01)	(0.01)	(22.52)	(37.29)
Fuel per Ha	-0.00	-0.00	-3.39***	1.50
	(0.00)	(0.00)	(0.88)	(1.45)
Electricity per cow	0.00	0.00	-0.42**	0.39
	(0.00)	(0.00)	(0.14)	(0.23)
Share protein in the diet	0.12	-0.07	-6782.4**	864.56
	(1.14)	(0.90)	(2264.2)	(3748.43)
Share of pasture	0.02	-0.06	-134.95	-32.56
	(0.06)	(0.05)	(128.93)	(213.44)
Age first calving	-0.00	-0.00	-6.15	-33.47*
	(0.00)	(0.00)	(8.93)	(14.79)
Biodiversity per Ha	0.01	0.00	-10.86	-15.47
	(0.01)	(0.01)	(13.69)	(22.67)

Herd's Renewal Rate	0.00	-0.00**	-8.28**	-1.40
	(0.00)	(0.00)	(2.87)	(4.75)
Share forage land	-0.02	0.36	-64.03	5220.6*
	(0.78)	(0.61)	(1542.32)	(2553.3)
Share temporary Pasture	0.10	0.16	-494.49*	1105.7**
	(0.11)	(0.09)	(224.07)	(370.96)
Length temporary pasture	-0.00	-0.00	-5.04	-8.39
	(0.00)	(0.00)	(9.04)	(14.96)
Days spent on pasture	0.00	-0.00	0.38	-0.46
	(0.00)	(0.00)	(0.46)	(0.75)
Livestock density	0.13	-0.04	-2552.6***	581.41*
	(0.07)	(0.06)	(147.49)	(244.17)
Mineral azote spread	0.00	-0.00	-9.77***	5.53
	(0.00)	(0.00)	(1.73)	(2.86)
Organic azote spread	0.00	-0.00	-7.21***	3.91
	(0.00)	(0.00)	(2.04)	(3.38)
Constant	-1.04***	0.51**	1448.17**	1286.78
	(0.24)	(0.19)	(483.30)	(800.12)
Observations	118	118	118	118
R^2	0.21	0.54	0.95	0.69
Adjusted R^2	0.08	0.47	0.94	0.64
Residual Std. Error (df = 100)	0.11	0.09	426.47	374.9

Note: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$