Working Papers SMART

Animal feed as a lever to reduce methane emissions: a micro-econometric approach applied to French dairy farms

Elodie LETORT, Pierre DUPRAZ

Working Paper SMART N°23-03

November 2023

UMR **SMART**, INRAE - L'Institut Agro Rennes-Angers

(Structures et Marchés Agricoles, Ressources et Territoires)

Les Working Papers SMART ont pour vocation de diffuser les recherches conduites au sein de l'UMR SMART dans une forme préliminaire permettant la discussion et avant publication définitive. Selon les cas, il s'agit de travaux qui ont été acceptés ou ont déjà fait l'objet d'une présentation lors d'une conférence scientifique nationale ou internationale, qui ont été soumis pour publication dans une revue académique à comité de lecture, ou encore qui constituent un chapitre d'ouvrage académique. Bien que non revus par les pairs, chaque working paper a fait l'objet d'une relecture interne par un des scientifiques de l'UMR SMART et par l'un des éditeurs de la série. Les Working Papers SMART n'engagent cependant que leurs auteurs.

Working Papers SMART aim to promote discussion by disseminating the research carried by SMART members in a preliminary form and before their final publication. These works have been accepted or already presented at a national or international scientific conference, have been submitted to a peer-reviewed academic journal, or are forthcoming as a chapter of an academic book. While not peer-reviewed, each of them has been read by a researcher of SMART and by an editor of the series. The views expressed in Working Papers SMART are solely those of their authors.

Animal feed as a lever to reduce methane emissions: a micro-econometric approach applied to French dairy farms

Elodie LETORT

INRAE, l'Institut Agro, SMART, 35000, Rennes, France

Pierre DUPRAZ

INRAE, l'Institut Agro, SMART, 35000, Rennes, France

Acknowledgement: *The authors would like to thank Luc Delaby for his agronomic expertise and Philippe Koutchadé for his advice on econometrics. This research was funded by the EU's Horizon 2020 program under grant agreement n° 770747 (LIFT project, https://www.lift-h2020.eu/). This work does not necessarily reflect the view of the EU and in no way anticipates the Commission's future policy.*

<u>Auteur pour la correspondance :</u>

Elodie LETORT
INRAE, UMR SMART
4 allée Adolphe Bobierre, CS 61103
35011 Rennes cedex, France
Email: elodie.letort@inrae.fr
Téléphone: +33(0)2 23 48 54 01

L'alimentation animale comme levier de réduction des émissions de méthane : une approche micro-économétrique appliquée aux exploitations laitières françaises

Résumé : L'objectif de cette étude est de simuler un système de paiement pour services environnementaux visant à réduire les émissions de méthane entérique par litre de lait en incitant les agriculteurs à modifier le régime alimentaire des vaches laitières. Nous avons estimé une fonction de rendement laitier en distinguant les types d'aliments fourragers et concentrés. Les émissions de méthane ont été calculées à partir de la relation technique entre les différentes sources d'alimentation et la productivité laitière. L'hétérogénéité des conditions de production des éleveurs a été identifiée à partir d'un modèle de mélange estimé par l'algorithme EM. Les résultats montrent qu'en introduisant un paiement pour services environnementaux, les agriculteurs réduisent d'autant plus leurs émissions de méthane par litre de lait que leur condition de production, reflétée par la qualité des fourrages, est bonne.

Mots clés : Exploitations laitières, technologie de production, hétérogénéité, système de paiement pour services environnementaux.

Classification JEL : Q12, Q54, C1

**Animal feed as a lever to reduce methane emissions:
a micro-econometric approach applied to French dairy farms**

Abstract: The objective of this study is to simulate a payment for environmental services scheme to reduce enteric methane emissions per litre of milk by incentivizing farmers to modify the diet of dairy cows. We estimated a milk yield function by distinguishing between types of fodder and concentrate feeds. Methane emissions were calculated from the technical relationship between different feed sources and milk productivity. The heterogeneity of the production conditions faced by the farmers was identified from a mixture model estimated by the EM algorithm. The results show that, with the introduction of the payment for environmental services, farmers reduce their methane emissions per litre of milk the more their production conditions, as reflected by the quality of their forage, are good.

Keywords: Dairy farms, production technology, heterogeneity, payment for environmental services scheme.

JEL classification: Q12, Q54, C1

Introduction

In France, 17.4% of greenhouse gases (GHG) are of agricultural origin on average over the last years. Cattle farming is the main contributor (60.4%), and methane from enteric fermentation of ruminants alone accounts for half of the GHGs emitted by dairy farms. Variations in methane emissions depend on herd management and production practices, including feed rations (Dall-Orsoletta *et al.* 2019). For example, increasing the level of animal production reduces methane emissions when expressed per litre of milk. The main cause is the lower share of the dairy cow basic requirements in its total feed requirements (Doreau *et al.* 2017). Systems based on optimized feed rations are often the most environmentally efficient (Henrikson *et al.* 2011), because it increases feed conversion efficiency, leading to higher productivity and reduced losses, especially in the form of methane. The nature of the diet of dairy cows can therefore modify the characteristics of the milk produced but also the quantities of methane emitted. For example, several studies have shown that supplementation with omega-3 fatty acids can reduce methane emissions from dairy cows (Martin *et al.* 2008; Nguyen *et al.* 2012).

Better management of animal feed is highlighted in the literature as an interesting lever to reduce enteric methane emissions and therefore GHGs. The objective of this study is to simulate a payment for environmental services scheme to reduce enteric methane emissions per litre of milk by incentivizing farmers to modify the diet of dairy cows and to evaluate their mitigation potential in tons of abated CO2 equivalent slaughtered. We propose a payment scheme targeted at enteric methane emissions, rather than all GHG emissions of the farm, because it is technically feasible to measure enteric methane emissions of dairy cows precisely through the chemical analysis of their milk. Indeed, an equation guaranteed by a patent (Weill *et al.* 2009) exists to estimate methane emissions per dairy cow based on their productivity and the fatty acid profile of the milk (Weill *et al.* 2008; Chilliard *et al.* 2009; Martin *et al.* 2008, 2009, 2010). This indicator may be an interesting basis to design results-based payments for environmental services. Although these schemes were theoretically more efficient – at least to induce farmer innovation – than action-based payments (Burton and Schwartz 2013; White and Hanley 2016; Engel 2016), few have already been implemented due to the difficulty of finding result indicators that are both reliable and simple to implement.

To do this, we estimate a milk yield function by distinguishing between types of fodder and concentrates and by assuming farmers choose the composition of the feed ration according to prices in order to maximize their gross margin per dairy cow. Our primal approach based on the estimation of a production technology allow us to calculate the implicit prices of non-marketed inputs, and their manipulation then allow us to simulate the environmental policies. To estimate the associated methane emissions, we do not have the fatty acid content of the milk produced on the farms, we will exploit another technical relationship between different feed sources and milk productivity to approximate methane emissions (Sauvant *et al.* 2011). The tested payment scheme will modify these production choices, favouring one or another diet, and will impact methane emissions per litre of milk. The analysis was carried out on dairy farms in western France, which is the first French dairy region, over the period 2007-2018 using the FADN database.

Many researchers in the microeconomics of agricultural production have estimated milk production technology. Some of them have estimated a technology of milk production using the stochastic frontier approach to analyse the heterogeneity of the efficiency of dairy farms and its impact on farm performance (Kumbhakar *et al.* 2009; Alvarez and del Corral 2010; Orea *et al.* 2015; Sauer and Paul 2013; Renner *et al.* 2021). Various methods explicitly accommodating the heterogeneity in a dairy production model have been used in the production literature. One of the methods widely used, because of its simplicity of implementation, is the *ex ante* classification into groups, based on *a priori* knowledge and assumptions about differences in technology. Farms are distributed according to exogenous sample criteria, such as intensification characteristics or system of production (*e.g.* on Finn dairy farms by Kumbhakar *et al.* (2008)). However, relevant technological characteristics may not be observed in the data. Random parameter econometric specifications enable us to consider unobserved heterogeneity. They are suitable for accurately estimating farm-specific behaviour but require complex estimation techniques (*e.g.* Koutchade *et al.* (2018) on French crop farms). Another approach is to build a latent class model, which assumed that each farm was associated with a particular technology group. The technology and the probability of farmers belonging to each technology group are estimated simultaneously. Such an approach combining the stochastic frontier method with a latent class model has often been applied to dairy farms (*e.g.* on Dutch dairy farms by Alvarez and del Corral (2010), on Danish dairy farms by Sauer and Paul (2013), on Spanish dairy farms by Orea *et al.* (2015) and on Swiss dairy farms by Renner *et al.* (2021)). These works generally interpret the difference between production technologies as a difference in intensification of practices. The descriptors of input intensity, production specialization or organic farming are either used directly as criteria to divide the sample (Kumbhakar *et al.* 2009) or used to determine the probability of farms belonging to a technological group (Alvarez and del Corral 2010; Sauer and Paul 2013; Renner *et al.* 2021). However, Renner *et al.* (2021) point out that the natural production conditions of the farms constrain them in a specific production technology. This finding implicitly suggests that the heterogeneity of production technologies may stem from the heterogeneity of production conditions. We suspect that production conditions, and in particular soil and climate conditions, have a very strong impact on the milk yield of dairy cows. Fodder quality plays a key role in explaining the variability of milk yields but also in the choice of feed ration made by farmers. A balanced feed ration necessarily requires an evaluation, even approximate, of the energy value of fodders to choose the type and quantity of adequate concentrate feed to supplement fodders. The quality of these fodders will depend mainly on soil and climatic conditions and is potentially heterogeneous between farms.

A better consideration of feed intake may improve the modelling of the behaviour of farmers on their farms. In addition, the analysis of methane emissions requires the consideration of the main components of the animal's feed ration (fodder corn, grass, and concentrates) since the nature of the ration will impact the emitted quantities of methane. Explicitly considering the feed ration can be tricky, especially because of the lack of data. Fodder and grass prices are never available in our databases on individual farms. In France, there are also no reliable indices informing us of the temporal and spatial evolution of these feed components. For example, Henry de Frahan *et al.* (2011) use such an index of concentrate prices by region to account for feed costs. The estimation of production technology in a primal framework also requires some variables that we generally do not have in our standard databases at the farm level, such as the amount of grass and the amount of fodder purchased and produced on the farm. Samson *et al.* (2017) seem to have this information in a specific database on Dutch dairy farms, which allowed them to estimate a milk production technology by distinguishing different components of the feed ration of feed cows. They develop a microeconomic model to analyse the technical relations between milk, fodder and manure production on Dutch dairy farms. They estimate a milk production technology in which the animal feed, dairy cows, labour and capital explain the milk production level. They specify a feed production function depending on concentrates, bought fodder and own produced fodder. A separated production function is specified for this on farm fodder that depends on applied animal manure, purchased chemical fertilizer and weather conditions. Although accounting for heterogeneity is not central in their approach, a farm-specific constant captures unobserved heterogeneity, which includes both farmer management quality and feed and livestock quality.

In our study, we also follow a primal approach and estimate the production technology for milk. Our work differed from Samson *et al.* (2017) in several ways. First, to address the lack of data regarding the diet of dairy cows, we propose a set of hypotheses built in collaboration with dairy production specialists to decompose the different sources of animal feed from the standard data at our disposal. We distinguish between concentrates, fodder corn (purchased and produced on the farm), and grass (ensiled and grazed). Second, we construct a production technology in which the output is the milk yield per cow and not the total amount of milk produced at the farm level. The decision mechanisms behind the analysis of the total amount of milk produced and the amount of milk produced per dairy cow are not the same. At the farm level, the farmer will modify his breeding practices, the number of dairy cows and his crop rotation to maximize the farm total profit in response to the incentives. Our approach attempt to investigate only the relationship between milk yield per cow and feeding decisions. This relationship is widely studied by scientists in animal sciences, who describe the physical mechanisms at play between the composition of a ration and its energy and protein content and the milk yield. Our approach relies heavily on animal sciences, which allow us to propose a specification of the production technology adapted to the reality of the farms in our sample. Third, we classify farms from a latent class model also named the mixture model to identify the technical relationship between the different components of the feed ration and the milk yield and to control for the heterogeneity of the production conditions of western French dairy farms. The estimation of a mixture model from the EM algorithm allow us to approximate the production conditions in which these farms produce milk. The originality of our approach is to extract the maximum information from the observed data, generated by known technical relationships but tainted by the behaviour of farmers and their heterogeneity. The results of our approach are convincing from the statistical, animal science and economic points of view, and their implications were interesting. In fact, we show that the dairy farms in western France do not have very heterogeneous behaviours. However, their production conditions are quite heterogeneous, which has a strong impact on the way farmers react to policy measures. With the introduction of the payment for environmental services, farmers who benefit from good production conditions, as reflected in quality fodder, reduce their methane emissions per litre of milk more significantly.

1. Milk production technology

First, we proposed a functional form of milk production technology that is consistent with animal science. Second, we proposed to use existing statistical methods to estimate the parameters of this production technology by controlling for farm heterogeneity.

1.1 Specification of the production function

The animal sciences specializing in dairy production consider in a simplified way that a dairy cow needs 6 UFL (Unité Fourragère Lait (Jarrige 1989) or Milk Fodder Units)[1] per day for maintenance and 0.48 UFL per kg of milk. The higher the yield of a cow is, the higher the energy requirement. Conversely, the milk yield y of a cow depends directly on the amount of feed dry matter she receives, in the form of fodder or concentrates, and on the energy content of these feeds. The energy content of the feed ration depends on the sources of the fodder. Grazed grass, for example, provides more energy than corn fodder (Hanrahan *et al.* 2018).

We considered that the daily feed ration of a cow for observation i (a farm a given year) is composed of the amount of dry matter provided by fodder corn x_{mi}, by grass x_{pi}, and by concentrates x_{ci}. To maintain flexibility in the relationship between the components of the feed ration, we assumed that the milk production technology can be represented by a quadratic form:

$$y_i = \alpha + \sum_{m=m,p,c} \beta_k x_{ik} + \sum_{k=m,p,c} \sum_{n=m,p,c} \beta_{kn} x_{ik}\, x_{in} + \epsilon_i \tag{1}$$

Where y_i is the milk yield per cow for the observation i, and ϵ_i is the error term of the model. To respect the concavity of the production technology, the Hessian matrix must be semi-definite negative. The marginal factor productivity must be decreasing, which means that $\beta_{mm} < 0$, $\beta_{pp} < 0$ and $\beta_{cc} < 0$. Additional feed input induces an increase in yield, but this increase decreases with the amount of feed input. The complementarity between fodder and concentrates, expressed by the parameters β_{mc} and β_{pc}, is not obvious, depending of the content of feed. For example, concentrates, especially protein-rich concentrates, usually complement fodder-based diets. However, concentrates can substitute for fodder.

An interesting feature of the dairy farming activity is that the feed choices made by dairy farmers seem to comply with the teachings and knowledge developed by specialists in animal production, who advise and inform technical institutes on the optimal feed rations to maximize milk productivity (Dou *et al.* 2001). In addition, farms equipped with robotic milking and automatic

[1] UFL is a unit to determine the energy value of a fodder for a dairy cow ration (1 UFL = 1700 kcalories).

feeding can control the balance of the feed ration on a daily basis (Thorup *et al* 2012). The technical relationship between milk yield and dry matter intake of dairy cows is assumed to be deterministic in the sense that animal science defines an explicit causal relationship under usual production conditions. The main sources of variation in the relationship estimated from our sample compared to this technical relationship is captured by error term. It would therefore be related to soil and climate conditions that can influence fodder production and quality, approximation errors in the calculated amount of fodder, and the management capacity of farmers.

Fodder quality plays a key role in explaining the variability of milk yields but also in the farmers' choice of feed ration (Weller and Bowling 2007). The higher the energy value of fodder is, the higher the ingestibility of the diet (Baumont *et al.* 2009). Other characteristics, such as the origin of this energy or their fatty acid composition, also have a role in the nutritional efficiency of fodders. Genetic choices, harvesting date, cultivation and conservation practices, and climatic conditions are the main factors at the origin of the high heterogeneity of corn and grass silages.

In our approach, we first consider that there is a technical relationship between the different components of the feed ration and the milk yield. Second, the heterogeneity comes mainly from the production conditions that impact the quality of the fodders from one farm to another and even from one year to another on the same farm. These production conditions include both soil and climatic conditions, as well as agricultural practices, such as the choice of seeds or the level of fertilization, which influences the energy content of the fodders. In the rest of the paper, we will discuss the heterogeneity in forage quality. In our approach, this implicitly referred to heterogeneous production conditions.

The identification of the different production contexts is possible thanks to a statistical technique described in the following section. Under the assumption that this technical relationship holds, our approach allowed us to control for the main source of heterogeneity of the farms and therefore normally to avoid potential endogeneity bias. A discussion of the potential endogeneity of input descriptors and the statistical tests of endogeneity will be carried out in the section describing the econometric estimation of the model.

1.2. Classification using a mixture model

We propose to build a finite mixed model, which is a type of latent class model. The finite mixture model is a widely used statistical method as a convenient way to model unknown data and to identify group structures (McLachlan *et al.* 2019). This model is generally estimated by the maximum likelihood method in using algorithm EM (Dempster *et al.* 1977), that is an iterative technique to approach the likelihood maximum of the parameters in the presence of unobservable latent variables.

Several papers use a latent class model to estimate the production technology of dairy farms (Kumbhakar *et al.* 2009; Alvarez and del Corral 2010; Orea *et al.* 2015; Sauer and Paul 2013; Renner *et al.* 2021). They generally assume that dairy farm production technologies are different according the level of farm intensification or specialization. They exploit available variables describing farm practices to distinguish between different technologies. The *a priori* probabilities parametrized in multinomial logit form then depend on the individual characteristics of the farms. In our case, we suppose that production technologies differ according to fodder quality. However, we do not have variables that allow us to approximate this quality. The use of the EM algorithm will allow us to classify our observations in groups without using any *a priori* information, except for the definition of the initial values (we will come back to this later).

Let r be the latent variable that characterizes the unobserved fodder quality of the farms. We considered K levels describing the fodder quality, according to their energy content. The probability that an observations belongs to group k is denoted ρ_k such that $P(r = k) = \rho_k$ and $\sum_k \rho_k = 1$. We consider that the *a priori* probability of belonging to a group is the same for all farms conditional on fodder quality. We assume that the milk production technology is different under different fodder qualities:

$$y_i = \mathbf{z}_i'\boldsymbol{\beta}^k + \varepsilon_i^k \text{ for } r_i = k \tag{2}$$

where $\mathbf{z}_i$ is the vector of explanatory variables in the model $[x_{im}, x_{ip}, x_{ic}]$, along with their cross and quadratic terms as defined in Equation 1; $\boldsymbol{\beta}^k$ is the parameters of the model associated with group k, and ε_i^k an error term following a normal distribution of variance-covariance matrix $\boldsymbol{\Sigma}_k$. We estimate the probability that each observation belongs to each group using the maximum likelihood method. The mixture model approach allows us to model the distribution of a random variable as the sum of several other simple distributions. The overall density function of milk yield is assumed to be a mixture of K sub-functions, according to the fodder quality. Therefore, we defined the density function $f(y_i; \boldsymbol{\Phi})$ as a convex combination of K density functions:

$$f(y_i;\mathbf{\Phi}) = \sum_k \rho_k\, f_k\big(y_i \mid r_i;\mathbf{\theta}_k\big) \tag{3}$$

where $f_k\big(y_i \mid r_i;\mathbf{\theta}_k\big)$ is the normal probability density associated with the group *k*, whose parameters are noted $\mathbf{\theta}_k = (\mathbf{\beta}_k, \mathbf{\Sigma}_k)$. The global parameter of the mixture is noted $\mathbf{\Phi} = (\rho_k, \mathbf{\theta}_k)$. Since the observations in the sample are independent of $i = 1, \dots, N$, the log-likelihood of this sample is defined by:

$$\log L(y;\mathbf{\Phi}) = \prod_{i=1}^{N} \log\Big(\sum_{k=1}^{K} \rho_k f_k\big(y_i \mid r_i;\mathbf{\theta}_k\big)\Big) \tag{4}$$

Since there is no analytical solution to this problem, the EM algorithm is generally used to estimate the parameters that maximize the likelihood. This is an iterative procedure in two steps. The Expectation step estimates the unknown data, knowing the observed data and the initial values of the parameters $\mathbf{\theta}_k$. The Maximization step maximizes the likelihood, made possible by using the estimation of the unknown data in the previous step. The parameters estimated in the Maximization step constitute the starting point for the Expectation step of the next iteration. We repeated these steps until convergence. See the paper of (reference) for detailed explanation. Once the estimation completed, it is necessary to assign each individual to the class to which it most probably belongs. To do this, we use Bayes' inversion rule:

$$\omega_{ik} = \frac{\rho_k f_k\big(y_i \mid r_i;\mathbf{\theta}_k\big)}{\sum_k \rho_k f_k\big(y_i \mid r_i;\mathbf{\theta}_k\big)} \tag{5}$$

It is then sufficient to assign each individual to the class for which the *a posteriori* probability ω_{ik} is the greatest.

The standard EM algorithm has several major limitations, and its results depend directly on the choice of arbitrary initial values for the number of groups and for the model parameters. The majority of the methods for estimating *K* groups use information criteria. An adequate method consists of selecting the *K* value that minimizes the AIC (Akaike, 1974) and/or the BIC (Schwarz, 1978). Concerning the initial parameters, we proceeded to a first classification of the observations and estimate a production technology for each class. The parameters of these different technologies are our initial parameters for the estimation by the EM algorithm. For the initial classification of the observations, we compared in a very simplified way the energetic needs and supplies calculated for each observation using animal science references. We assumed that a large difference between needs and supplies at the farm level indicates either higher or lower energy content of the dry matter (fodder quality), depending on whether supplies were greater or smaller than needs. We then ranked the observations according to our *a priori* assessment of fodder quality. This calculation based on animal science charts served to define the initial parameters used in the EM algorithm.

2. Production choice model of breeders

In this section, we describe the technology-constrained profit-maximization program for farmers and the model solution that enabled us to derive the feed demand equations. We also describe the simulated payment scheme.

We modelled only the choice of dairy farmers in terms of feed. We did not consider their decision in terms of acreage allocation and farming practices, which is of course underlying their feeding decision, nor their decision in terms of cattle herd size and structure. We assumed that dairy farmers decide on the composition of the dairy cow feed ration in a way that maximizes their gross margin per dairy cow π_l under the technological constraint described in the previous section. Therefore, farmers must decide how much concentrate to feed per cow x_c at price w_c, as well as how much fodder per cow can come from corn x_m or grass x_p. The composition of the feed ration by the farmers depends on the costs of each feed source w_c, w_m and w_p and implicitly on their energy content to balance the feed ration and optimize their margin per cow. The combination of these different feed sources allows the farmer to achieve milk yield y_l, which is sold for price y_l. The farmer's optimization program is as follows:

$$\max_{x_c, x_m, x_p} \pi_l = y_l p_l - w_c x_c \ - w_m x_m - w_p x_p \tag{6}$$

$$s.c.\, y_l = \alpha + \sum_{m=m,p,c} \beta_k x_k + \sum_{k=m,p,c} \sum_{n=m,p,c} \beta_{kn} x_k\, x_n + \epsilon \tag{7}$$

Feed components are in tons of dry matter per cow per day, and milk yield is in litres per cow per day.

We sought to simulate a public policy tool that is optional for farmers to incentivize them to reduce enteric methane emissions. We focus on a payment for environmental services scheme, in which farmers receive a payment proportional to their reduction in methane emissions. In addition to compensating for the additional cost or loss of profit, such as most of the agri-environmental and climate measures (MAEC) of the Common Agricultural Policy (CAP), this system rewards the result in terms of emission abatement. Result-based schemes are more convincing for private payers such as companies or environmental associations. On the farmer's side, no prescribing specific measures can induce farmer innovation. On the regulator's side, results-based payment are less cost-effective than actions-based payment in a context of imperfect information (White and Hanley 2016). Different payment amounts, expressed in € per kg of abated methane per litre of milk, are simulated. To calculate the evolution of enteric methane emissions at the farm level, and in considering possible changes in the number of dairy cows, we assumed a constant milk production per farm. This hypothesis seems appropriate for our study period, characterized by the existence of milk quotas until 2015.

We modify the gross margin of the farmer to integrate the payment granted to the farmers:

$$\pi_l = y_l\left(p_l + p_{ch_4}\Delta ch_4\right) - w_c x_c - w_m x_m - w_p x_p \quad (8)$$

where p_{ch_4} is the premium proportional to the reduction in CH4 emissions in € per kg of abated methane and Δch_4 is the change in methane emissions per litre of milk from the baseline without payments. In the baseline situation, we have $p_{ch_4} = 0$, which is equivalent to Model (1). According to Sauvant's equation, the amount of methane emitted en g/kg MOD (digestible organic matter) depends on the total amount of dry matter as a % of dairy cow live weight $MSIPV$ and the share of concentrates in this total PCO. This gives the following formula:

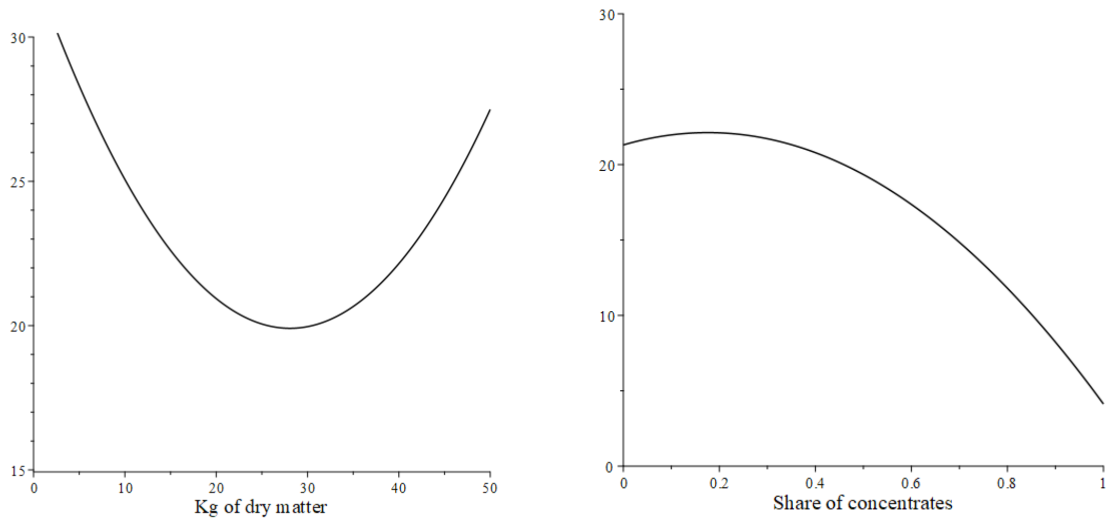
$$CH_{4_{mod}} = 45.42 - 6.66MSIPV + 0.75MSIPV^2 + 19.65PCO - 35PCO^2 - 2.69MSIPV \times PCO \quad (9)$$

The total amount of dry matter is equal to the amount of dry matter contributed by corn, grass and concentrates. A live weight of 600 kg is assumed. The share of concentrate is equal to the amount of concentrate on this total amount of dry matter. Enteric methane emissions expressed in g/kg MOD are converted in g/kg DM (dry matter) from this relationship $CH_{4_{DM}} = \left(CH_{4_{mod}} - 4.68\right)/1{,}32$ (Sauvant *et al.* 2015). The amount of methane is then expressed in g per kg of dry matter. To obtain emissions in g per dairy cow, $ch_{4_{DM}}$ is multiplied by the total amount of dry matter ingested per dairy cow, and to obtain emissions in g per litre of milk, it is further divided by the total milk production per dairy cow, according to this equation:

$$CH_4 = \left(CH_{4_{DM}} \times MSI\right)/y_l.$$

The quantification of methane emissions depends on the unit in which the emissions are measured. Figure 1 shows the evolution of methane emissions in kg of dry matter according to the variables used in Sauvant's equation, the total quantity of dry matter and the share of concentrate in this total quantity. Methane emissions per amount of dry matter decrease with increasing fodder and concentrate intake per cow, but the decrease is less and less until the optimum amount of dry matter that minimizes emissions is reached. The decrease in emissions is greater when increasing the amount of fodder rather than concentrating. Since fodder is composed of grazed grass, silage, and corn, and grazed grass has a higher energy content than corn and silage, this suggests that increasing the amount of grazed grass in the diet can decrease methane emissions per kg of dry matter.

Figure 1: Evolution of methane emissions in g per kg of dry matter



Note: In the first graph, the share of concentrates is fixed at its average level observed in the sample. In the 2nd graph, the total amount of dry matter is fixed at its average level observed on the sample.

Conversely, calculated methane emissions per dairy cow increase with increased feed intake. However, for a given amount of dry matter, they decrease with an increase in the proportion of concentrates in the diet. Finally, when methane emissions per litre of milk are analysed, the analysis of the emissions evolution becomes more complex as it also depend on the evolution of yield and thus on the marginal productivity of fodders and concentrates estimated in the previous step.

The derivation of the first-order conditions allows us to derive the optimal demand equations for the quantities of concentrates, corn fodder and grass, which depend on the price of concentrates, of corn, grass, and the amount of aid $x_c^*(w_c, w_m, w_p, p_{ch_4})$, $x_m^*(w_c, w_m, w_p, p_{ch_4})$ and $x_p^*(w_c, w_m, w_p, p_{ch_4})$. The optimization of the program does not easily allow us to analytically calculate the optimal dry matter quantities since Δch_4 depends on the dry matter quantities to the third degree and is divided by y_l, which also depends on the dry matter quantities. We therefore solved the optimization program by numerical simulation. Since we did not have the prices of the factors of production, we used their implicit prices to perform the simulations. In fact, the estimation of the parameters of the production technology allows us to calculate the dual prices corresponding to the marginal values of the different sources of animal feed (concentrates, forage corn, grass). By adding input non-negativity constraints, we obtain, for each simulated payment amount, a single technically feasible solution given the intake capacities of dairy cows.

3. Estimation of the model

In this section, we describe the data used to estimate the milk production function and assess methane emissions from each farm. The results of our approach are discussed and compared to standard results in animal science.

3.1. The data

We investigated a sample of dairy farms located in the north western regions of France, producing 50% of the French milk production, from the FADN database, which contains 3,668 observations over the period 2007-2018. Table 1 provides some descriptive statistics of our sample.

First, we calculated the components of the dairy cow's feed ration from the variables available in the FADN. Our approach was based on the knowledge and expertise of specialists in dairy production. Based on the number of dairy cows and other cattle, we allocated the share of the main fodder area devoted to the feeding of the dairy cows. We considered that a dairy cow consumes twice as much fodder as other cattle (heifers and other cattle) and that a heifer consumes twice as much grazed grass as a dairy cow. The quantity in tons of dry matter of corn silage produced on the farm was obtained by multiplying the area of corn fodder (allocated to dairy cows) by the yield in tons of dry matter per hectare (obtained from French statistics published by the Ministry of Agriculture, Agreste). We assumed that 8% of the dry matter obtained was lost and not consumed by the animals. We also considered the quantities of corn silage purchased. Next, we assumed that the grassland was mowed to provide grass silage or grazed directly by the cows. We estimated the duration of grazing from the area of grassland.

We considered that it takes at least 0.20 hectares of grassland for a cow to graze for two months. Below 0.20 hectares per dairy cow, the cows never graze. Considering that a cow can ingest 16 kg of DM per day, the total amount of dry matter in tons of grazed grass is calculated by multiplying the duration of grazing (in days) by 0.016 by the number of dairy cows. Then, the amount of grass silage was calculated as the total amount of grass produced by the grassland minus the amount of grass grazed by the cows. We assumed that 15% of the dry matter obtained is lost and not consumed by the animals. Finally, we have the amount of concentrate in kg produced and purchased at the farm level. We assumed that this concentrate is composed of soybean meal and cereals. Since the dry matter content is approximately 87% for both soybean and cereals, we can calculate the amount of concentrate in tons of dry matter. Finally, the milk yield was calculated simply by dividing the total milk production by the number of dairy cows on the farm.

Table 1: Descriptive statistics (per day and per dairy cow).

	Mean	Standard deviation	Minimum	Maximum
Milk yield	19.58	2.93	6.36	23.76
Quantity of corn fodder (kg DM*)	9.73	2.98	0	20.41
Quantity of grass (kg DM)	4.44	2.22	0.44	19.63
Quantity of concentrates (kg DM)	2.18	0.88	0.12	6.56

** kg DM: kilogram of dry matter*

3.2. Econometric issues

Estimating the mixture model from the EM algorithm presented earlier allowed us to estimate the individual probability of each observation belonging to each of the classes. However, to do this, we must first determine the number of groups. Several estimates using the EM algorithm have been tested with a different number of classes. The comparison of the AIC and BIC criteria drove us to retain the number of 3 classes. We obtained the following distribution: 27% of observations belong to the first group, 67% to the second group and 6% to the third group. We assumed that the unobserved heterogeneity at the origin of the construction of these classes was mainly due to the soil and climatic conditions faced by the farmers each year and that impact the energy content of the fodder. We used the results of the empirical application to better describe these groups and to confirm the role of fodder quality on milk yield.

The suspected endogeneity of the production factors is a recurrent problem in the estimation of primal production functions. Unobserved factors, such as climate or soil quality, can simultaneously influence milk yield and the farmer's choice of production factors. Samson *et al.* (2017) consider all their variable inputs endogenous and use the fixed effects instrumental variable generalized method of moments to estimate their technological function. In our model, the potentially endogenous inputs were the quantities of corn fodder, grass and concentrates fed to the animals. However, the quantities of grass and fodder are not determined by weather conditions of the farms observed in the current year (the year of milk yield) since they are calculated from the average yield of the department and the cropping decisions made by the farmers the previous year. We therefore assumed that these descriptors are exogenous in our model. Concerning the concentrate quantity, we realized the Wu-Hausman test to detect a potential endogeneity problem. Its implementation was simple using the augmented regression technique. In a first step, we regressed the potential endogenous variable by a set of instrumental variables, in our case, the explanatory variables of the model plus other exogenous variables such as the price of milk. In a second step, we estimated the milk yield technology by introducing the residual of the first step regression as an explanatory variable in addition to the assumed biased variable. If the residual was not significant, the variable did not appear to be endogenous. Performing this test on our sample suggested that the amount of concentrate per dairy cow is not endogenous in our model. This may derive from the fact that we estimated the milk yield per dairy cow and not the milk production at the farm level. This result was also consistent with the way we view our model as a technical relationship that exists between feed intake and milk yield. Additionally, estimating our technology from a mixture model allows us to control for potential sources of unobserved heterogeneity that can induce on type of endogeneity problems.

3.3. Milk production technology

In this section, we estimate different production technologies, while considering whether the observations belong to the classes presented in the preceding Section 3.2. Our objective in comparing these different models was to select the model specification that best fit our sample. The estimated parameters of the different models are shown in Table 2.

The first column corresponds to the model composed of a single production technology estimated by the ordinary least squares on the whole sample without considering the unobserved heterogeneity. From one year to the other, the farmers face different production conditions that are more or less favourable to milk productivity. Theoretically, these production conditions should have an impact on both the quantities of fodder produced and their quality. This suggested that a better fit may come from estimating a different production technology per group, which corresponds to our second model (columns 2, 3 and 4). However, in practice, the quantities of corn and grass calculated from available data depend on average aggregate yields and cropping decisions made the previous year and therefore depend on production conditions that are different from those that affect the current year's milk yield. We can therefore postulate that soil and climatic conditions will mainly influence the energy content of the animals' feed ratio, which is reflected in the model constant. In microeconometric analysis of dairy farming, a farm-specific constant can be incorporated to capture the differences in land quality (Helming *et al.* 1993; Sauer *et al.* 2013). In our approach, the constant captures differences in fodder quality that were not farm specific, as they can vary from year to year. We explicitly proposed defining this effect in the constant by incorporating a group-specific constant in the production technology (model 3). For this, we constructed a dummy variable for each group D_k that is equal to 1 if the observation belongs to Group k. The estimated production technology thus takes the following form:

$$y_l = \sum_k \alpha_k D_k + \sum_{i=m,p,c} \beta_i x_i + \sum_{i=m,p,c} \sum_{i=m,p,c} \beta_{ij} x_i \, x_j + \varepsilon \qquad (10)$$

If the unobserved heterogeneity is related to differences in fodder quality, we should have a constant that breaks down as $\alpha_k = \gamma + \mu \, q_k$, with the constant γ being the same for all observations corresponding to the maintenance requirement of a dairy cow, and the impact μ of fodder quality q_k on milk yield, with fodder quality being different for each group. According to dairy specialists, the energy content of fodders ranges from 0.7 to 0.9 UFL per ton of dry matter, depending essentially on the composition of the feed ration, climatic conditions, and fertilization of the fodders.

The estimation results favoured the third model, that is, the one with the individual constant for each group, described by Equation (10). First, the R2 obtained by estimating a production technology without taking into account the unobserved heterogeneity captured by the groups (model 1) is 0.31. It increased to 0.76 when we introduce a different constant for each group of observations (model 3). This is a great improvement with only two additional parameters. By estimating one production technology per group, the R2 values were between 0.51 and 0.71 (model 2). Then, all the parameters of the production technology of model 3 are significantly different from 0 at the 1% threshold. The signs of the parameters are consistent with animal science references and respect all the concavity conditions, which is not the case for the other models. The signs of the parameters correspond to those expected. An increase in the amount of feed induces an increase in yield ($\beta_c > 0$, $\beta_m > 0$ and $\beta_p > 0$), and the yield increase decreases with the amount of feed ($\beta_{cc} < 0$, $\beta_{mm} < 0$ and $\beta_{pp} < 0$). Compared to model 1, the differentiation of the constant by group allows us to better identify the substitution effects between concentrate and fodders, either grass or corn. Finally, from model 3, it is possible to calculate the parameters γ and μ, which are identical for all observations and in agreement with consistent energy density levels, classically between 0.7 and 0.9 UFL per ton of dry matter. Indeed, when $\gamma = -30.8$ and $\mu = 47.35$, the constant equal to 7.44 corresponds in this case to an energy density of 0.8, which corresponds to the standard energy density level of a food ration (Velmorel and Coulon 1992). The constant equal to 11.79 corresponds to an energy density of 0.9, which is the upper bound of the energy density of a ratio. The constant equal to 2.32 corresponded to a constant of 0.7, which is the lower bound of the average energy density of a ratio. The point of this very simple calculation is not to define the energy content of the forages in each group. Moreover, we do not use these values in the rest of the paper. The interest of this calculation is just to be able to associate a level of forage quality (high, medium, low) to each of the groups built by the EM algorithm, and to verify our model and our initial hypothesis (that the quality of the fodders plays an important role in the variability of the milk yield).

Table 2: Parameters estimated from the different models

	Model 1	Model 2			Model 3
		Class 1	Class 2	Class 3	

α	7.57***	3.48***	8.25***	0.91	-
Class 1	-	-	-	-	11.79***
Class 2	-	-	-	-	7.44***
Class 3	-	-	-	-	2.32***
β_c	3.28***	8.06***	1.77***	4.48***	2.71***
β_m	0.69***	0.95***	0.58***	0.50*	0.63***
β_p	0.74***	1.75***	0.52***	1.16***	0.54***
β_{cc}	-0.32***	-0.76***	-0.18***	-0.53***	-0.29***
β_{mm}	-0.02***	-0.02***	-0.02***	-0.01	-0.02***
β_{pp}	-0.03***	-0.06***	-0.02***	-0.01	-0.02***
β_{mp}	-0.03***	0.004	-0.03***	-0.04*	-0.03***
β_{mc}	0.02	-0.11***	0.11***	0.08*	0.06***
β_{pc}	-0.007	-0.52***	0.11***	-0.26***	0.05***
R^2	0.31	0.51	0.71	0.67	0.76
Number	3 668	983	2 455	230	3 668

Note: as a reminder, the index c corresponds to the concentrates, the index m to the fodder corn and the index p to the grazed and/or ensiled grass. Class 1 corresponds to high fodder quality, class 2 to medium fodder quality and class3 to low fodder quality.

This validated model 3 developed in Equation (10) suggest that the observations in Group 2 with the constant equal to 7.44 are characterized by average fodder quality. This is confirmed by the closeness of the results to the production technology estimated on the full sample in model 1 and that estimated on group 2 in model 2. The observations of group 1, with the constant estimated at 11.79, are characterized by high fodder quality compared to the standard quality. In contrast, the observations of group 3 are characterized by lower fodder quality. Comparing the characteristics of the groups, it can be observed that the farmers who produce fodders with a high energy value are also those who use the least amount of concentrate per cow. This is consistent with the recommendations of animal science to maximize the feed value of fodders to limit the use of supplementary feeds and reduce production costs.

Our results suggested that the differences in farmers' feeding behavior are mainly due to the heterogeneity of production conditions. Their fodder quality, which tells us about their production conditions, are heterogeneous from one farm to another and even from one year to another. Our results show the importance of trying to understand the behaviour of farmers thanks to the support of technical sciences (animal sciences and agronomy) to specify our economic model as much as possible. The results of a poorly specified model, even when estimated using the most advanced statistical and econometric techniques, will be difficult to interpret from an economic and zootechnic point of view.

4. Simulation results

Once all model parameters are estimated, we simulated the payment scheme. The greenhouse gas emission reduction potential was expressed in €/tonne of CO_2 equivalent. The IPCC considers that one ton of methane (CH_4) has a global warming potential 28 times higher on average than one ton of CO_2 over a period of 100 years. Therefore, each ton of methane is worth 28 tons of CO_2 equivalent (CO_2e) in GHG emission budgets. On average, it takes 22 g of CH_4 to produce 1 litre of milk (between 19 and 25), or approximately 0.6 kg CO_2e/litre; 130 kg of CH_4 per cow (between 88 and 177), or 3.6 t CO_2e/cow/year; and 8.5 tons of CH_4 per farm per year (between 2 and 35), or 240 t CO_2e per farm per year.

In this first approach, we assumed that the demand for milk was constant. This means that it is supposed to be rigid enough that any small changes in the milk average cost and price due to the scheme will not displace the market equilibrium significantly. Under this assumption, the payment program aims at the substitution of milk production with higher methane emissions by production with lower emissions. Even if the simulated scheme generates a variation in milk yield, we assumed that farmers modify their cow numbers to maintain a constant milk production. Based on this assumption, we can say that an average decrease of 10% in methane emissions per litre of milk or on a farm scale corresponds to an average decrease of 24 tons of CO_2 equivalent per farm and per year.

4.1. Premium for Reducing Enteric CH4 Emissions per Litre of Milk

We simulated a premium for the reduction of CH_4 emissions per litre of milk. The objective of this system was to encourage farmers to replace milk production that is not very climate-friendly with more climate-friendly production by offering them a better way to use their milk. The farmer does not simply choose the composition of the feed ration that reduces his methane emissions. To optimize the amount of his premium, he also considers the impact of his ration on the yield of milk and the impact of the yield on methane emissions. One might expect that this system would encourage farmers to increase their yield since each additional unit of milk produced is valued. Their strategy in terms of feed composition, described in table 3, differs depending on the energy content of their fodder.

When farmers produce average quality fodders, this premium induces several changes in the composition of the cows' feed ration: they increase their share of concentrate in the ration, slightly increasing the use of concentrates and strongly decreasing the total amount of fodder, mainly grass. The amount of total dry matter provided to the cows is reduced but becomes more dependent on concentrates. This ration composition allows them to maintain a stable yield but to reduce emissions per litre of milk. When farmers face poorer production conditions, they produce lower quality fodders. In this case, to produce less-emitting milk, they seek to increase their yield and not to decrease the quantity of dry matter brought to the animals, which is already low in energy. To do so, they strongly increase their use of concentrates to the detriment of the grassland. In this case, the significant increase in concentrates is accompanied by an increase in the farm production of corn fodder. Finally, when farmers produce higher quality fodders, their feeding strategy is even different. To reduce methane emissions per litre of milk, farmers agree to reduce their yields and decrease the amount of dry matter fed to their animals, including the amount of concentrates. The decrease in grassland is proportionally less than in other fodder contexts.

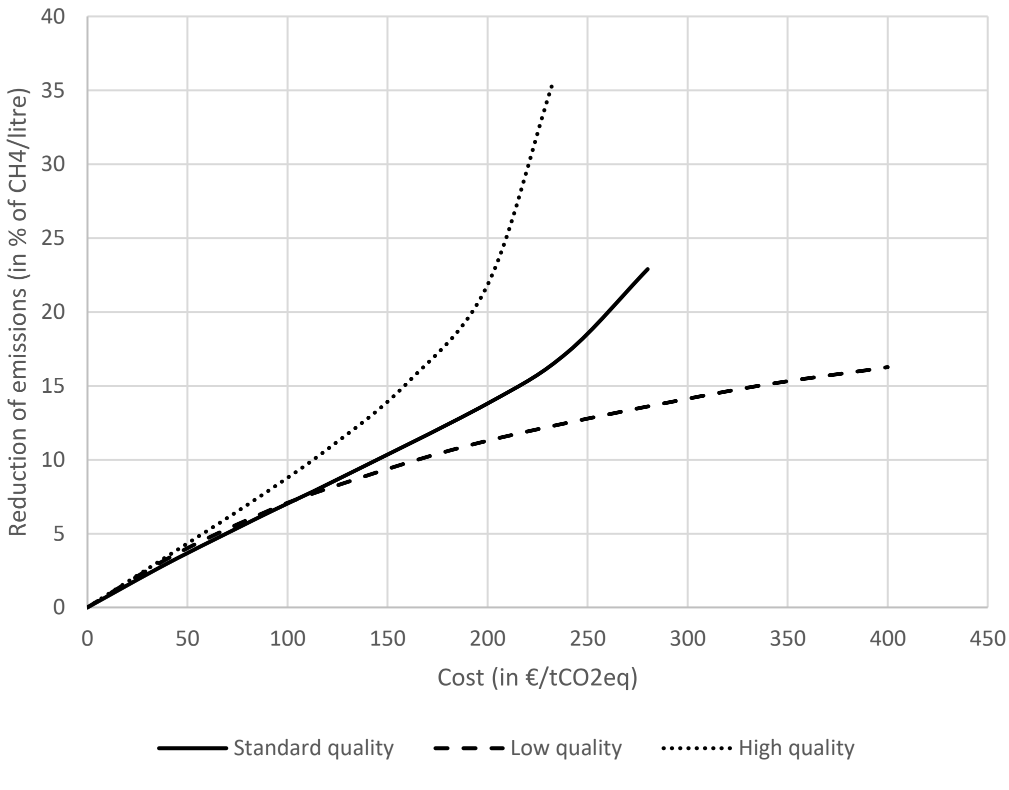
Table 3: Strategy in terms of feed composition according the quality of fodders.

	Share of concentrates	Total amount of fodder	Grassland	Milk yield
Low quality	+	=	-	+

Standard quality	+	-	-	=
High quality	-	-	-	-

Figure 2 represents the abatement costs in € per ton of CO2 equivalent of CH4 emissions per litre of milk induced by this payment scheme. It is interesting to note that, for the same emission reduction, the costs are different depending on the fodder quality. For a cost of €200/CO2e, farmers with high fodder quality achieve on average a 22% reduction in methane emissions per litre of milk, compared to 14% for those with average quality fodder and 11% for those with lower quality fodder. These abated emissions increase with the cost of implementing the payment scheme. The reduction in emissions can reach 35% when farms have good quality fodders.

Figure 2: CH4 emissions reduction in % according to abatement cost and fodder quality



Our results demonstrate the importance of seeking better feed quality to improve feed efficiency and thus reduce methane losses. This result was validated by the animal science literature, which has already shown that improving the quality of feed, both fodders and concentrates, improves feed efficiency and thus lower enteric methane emissions. Leng (1993) estimated that 75% of global CH4 emissions from ruminants came from ruminants grazing poor quality feed. Van

Middelaar *et al.* (2014) evaluated the potential cost of three feed quality altering strategies: (1) dietary supplementation of an extruded flaxseed product, (2) dietary supplementation of a nitrate source, and (3) reduction of the maturity stage of grass and grass silage. Using a linear programming model of a dairy farm, they estimate that reducing grass maturity is the most cost-effective: 57 €/t CO2e versus 241 €/t CO2e for nitrate supplementation and 2,594 €/t CO2e for flax seed supplementation. For dairy farms in Ontario, Hawkins *et al.* (2015) estimate that a change in feed ratio can achieve a 5.3% decrease in methane emissions at low cost (€20 Mg-1 CO2e). For reductions beyond the 5% level, the cost is estimated at approximately 415€ Mg-1 CO2e. In their view, little room for manoeuvring exists because the diets of these farms are already characterized by high concentrate intakes.

To illustrate how much heterogeneity in fodder quality matters, we simulated the same scenario, but this time, we used the production technology estimated on the full sample without distinguishing the three different classes of fodder quality. The results of the simulations were very different from those obtained by our approach, particularly the impact on the grassland area. The simple model largely underestimated the decrease in grassland induced by the payment scheme: for the same reduction in emissions, the estimated decrease in grassland area is divided by two. This means that the expected environmental and economic consequences of such a scheme might be highly biased when the heterogeneity of fodder quality is ignored. This importance of heterogeneity probably holds about the evaluation of any public policy tools that target agriculture.

4.2. Premium combinations to enhance grassland

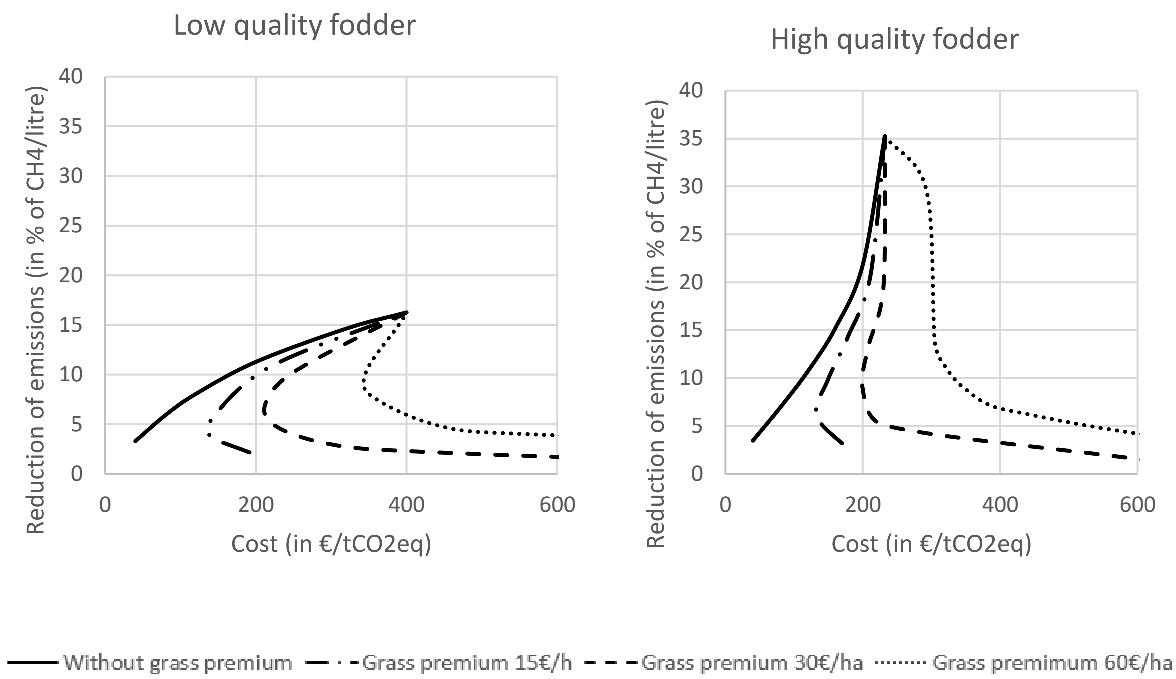
The literature agrees on the need to improve the energy content of the diet to improve feed efficiency and reduce methane losses. In our sample, improving the energy content of the ration involves increasing the proportion of concentrates in the total amount of dry matter fed to the cows. This increase in concentrates accompanies a sharp decrease in the area allocated to grassland. However, the benefits provided by the grassland are poorly taken into account in our approach. The impact of grazing on methane emissions is quite complex. On the one hand, a cow that grazes or feeds mostly grass produces less milk on average, and therefore, the amount of methane produced per litre of milk is greatest for grass-fed systems. On the other hand, the addition of grass to a ration directly improves the nutritional quality of milk by increasing the content of polyunsaturated fatty acids, which can reduce methane emissions (Martin *et al.* 2008; Nguyen *et al.* 2012). In any case, given the many environmental benefits provided by grassland, such as water quality and biodiversity, the negative impact of the simulated premium on grassland is not desirable. Indeed, the use of pasture reduces the need to grow, harvest, and store fodders on the farm. This means less machinery, fuel, and fertilizer and thus fewer CO2 emissions in grazing systems (Knapp *et al.* 2014). Grassland is also a carbon sink, capturing more CO2 than it emits. Dutreuil *et al.* (2014) found that total GHG emissions from conventional U.S. dairy farms were reduced by 27.6% while maintaining milk production and increasing net returns by 29.3% when cows were allowed to graze part of the year. Hawkins *et al.* (2015) estimate a decrease in enteric methane emissions from a change in dairy cow diets in Ontario, but this is only a small fraction of the total GHG emission reduction. Vellinga and Hoving (2011) reported that the loss of soil carbon from ploughing up grasslands for corn silage is greater than the decrease in enteric methane production achieved by switching to a more digestible corn-based diet.

For an analysis of the overall environmental performance of livestock operations, it would be necessary to extend the model to include crop rotation choices, cattle numbers, and cropping practices, such as nitrogen fertilization, to assess the impact of production decisions on the total amount of GHG emissions produced per farm. In the context of this study, we can however provide some insights by simulating a new payment scheme that would reduce enteric methane emissions per litre of milk while maintaining or even increasing the proportion of grassland in the feed ration. The idea is to combine the premium associated with the reduction of emissions per litre of milk with a premium per hectare of grassland.

We simulated three levels of premium per hectare: 15€, 30€ and 60€. Assuming an average grassland yield, these aids are equivalent to a premium of 0.0065, 0.013 and 0.026€/kg of dry matter. Therefore, they were introduced in our model as a decrease in the cost of grassland management. We combined these aids with premiums associated with the reduction of emissions per litre of milk. Figure 3 shows the evolution of the reduction in methane emissions in % as a function of the cost of setting up these premiums in €/teqCO2. The graph on the right shows the potential reduction in emissions when the fodders have a high energy content, while the graph on the left shows the potential reduction when the fodders have a low energy content. The solid curves represent the results without premium and are thus identical to those presented in Figure 2. The three premium levels are represented by the dotted curves.

We observed that for the same abatement cost, the reduction in emissions can be different depending on the feeding strategy chosen by the farmers. For example, in the case of a 100€/ha premium and low-quality fodders, for a cost of 300€/tCO2eq, a 12% reduction in emissions can be achieved by reducing the amount of grass in the ration by 50% or a 3% reduction in emissions with a 12% increase in the amount of grass. The reversal points of the curves correspond to the change in feeding strategy at which the amount of grass stops increasing and starts to decrease in the diet. Two interesting points emerge from these results: (1) when the feeding strategy is based on grass, regardless of the level of the grass premium, the evolution of cost-based emissions no longer depends on fodder quality; (2) under certain conditions, a large decrease in emissions can be achieved without decreasing the grassland. These conditions are that the amount of the grass premium must be sufficiently high (at least 60€/ha), and the fodder must be of good quality. In this case, for a cost of approximately 300€/tCO2eq, one can achieve a decrease in methane emissions per litre of milk between 10 and 30% depending on the composition of the food ration. For example, a decrease in methane emissions of approximately 15% may be achieved by increasing the grassland by approximately 15%. This is accompanied by a sharp reduction of almost 30% in the amount of dry matter fed to the cows and a decrease in yield of only 15%. Without seeking an increase in grassland but maintaining it at its initial level, our results suggest that this combination of premiums can achieve a reduction of almost 30% in emissions.

Figure 3: CH4 emissions reduction in % from a combination of premiums



Conclusion

In this study, we proposed to specify and estimate a milk yield function for French dairy farms based on FADN accounting data. Our approach combine animal science knowledge and references, the exploration of the panel data of our sample, and the use of adapted statistical methods. For example, the results issued from animal science charts serves to define the initial parameters used in the EM algorithm. It enabled us to obtain an econometric specification of the production technology, which fits very well with our sample. We showed that the dairy farmers in our sample have rather homogeneous economic behaviour. However, their fodder quality was highly heterogeneous due to the heterogeneity of the production conditions they face, which has a strong impact on the way farmers react to policy measures.

The main limitations of our approach concern two points. First, the composition of the cows' feed ration is calculated from available individual variables and a set of assumptions constructed in collaboration with dairy production specialists. Although the consistency of dry matter quantities and milk yields are verified for each farm, we can assume that there are measurement errors on the components of the feed ration, which may bias our estimation results. Second, differences in dairy cow productivity between farms can be due to heterogeneity in forage quality, but also to the genetics of the dairy cows. Yield potential and feed efficiency can be very different from one breed to another. We consider that this assumption can be justified since our study focuses on farms located in the western part of France, characterized by a relatively intensive agriculture. In this area, 80% of the dairy cows are Prim'Holstein cows, chosen for their good dairy performance.

We simulated the effects of a result-based payment scheme targeting the GHG abatement performance of dairy cow management. The advantage of simulating this scheme was to identify the strategies in terms of animal feeding that farmers would select to maximize their margin. Our results showed that improving the energy value of the feed ration is necessary to reduce enteric methane emissions per litre of milk. This increase in the energy value of the ration is achieved either by increasing the proportion of concentrates in the ration or by improving the quality of the fodder. We also showed that for a cost between 250 and 300€/CO2e, a decrease in enteric methane emissions per litre of milk between 15 and 30% was possible without decreasing the grassland area. This result was consistent with the target value of CO2 set at 250€/tCO2eq in 2030 (Quinet Commission). However, this environmental objective is achievable under certain conditions: farmers must have good quality fodder and receive a premium proportional to the reduction in methane emissions per litre of milk, as well as a grass premium to encourage them to maintain their grassland area.

The improvement of fodder quality is an important and problematic issue. Indeed, quality is very dependent on climatic hazards but also on livestock practices. However, the fertilization practices of fodder crops and the water requirements of corn crops are challenged by the environmental requirements faced by livestock farms, including objectives in terms of GHG emissions associated with emission of fertilizer production and carbon sequestration in grassland soils. Biodiversity and water quality are major stakes for agriculture. For instance, early harvesting practices, by limiting flowering, are unfavourable to biodiversity (Beaumont *et al.*).

Substituting part of the concentrates with a flax-based concentrate, which is very rich in omega 3, is also an issue studied to improve feed efficiency. A study by Martin *et al.* (2008) showed that the decrease in methane emissions is proportional to the amount of flax added to the diet, with decreases ranging from 15 to 40% following flax additions of 5 to 15% dry matter. This strategy is also problematic because, assuming this effect holds, the cost of flax-based concentrates is very high, and a payment scheme funded by individuals or communities that favour a concentrate-based system is highly questionable. An example of a very similar scheme exists in France (Marette and Millet 2014). Farmers feed their dairy cows flax-based concentrates, in return for which they receive a payment financed by private donors if their level of methane emissions does not exceed a certain target set by agricultural region. They also have the possibility to sell their agricultural product under the "Bleu-Blanc-Coeur" label, which promotes the health benefits of omega-3-rich feed. Finally, the percentage of farmers participating in this "eco-methane" program is very low, particularly because the amount of remuneration is much lower than the additional cost of purchasing flax-based feed.

References

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

Baumont, R., Aufrere, J., Meschy, F. (2009). La valeur alimentaire des fourrages : rôle des pratiques, de culture, de récolte et de conservation. *Fourrages*, 198: 153-173.

Burton, R.J., Schwarz, G. (2013). Result-oriented agri-environmental schemes in Europe and their potential for promoting behavioural change. *Land Use Policy*, 30(1): 628-641.

Chilliard, Y., Martin, C., Rouel, J., Doreau, M. (2009). Milk fatty acids in dairy cows fed whole crude linseed, extruded linseed, or linseed oil, and their relationship with methane output. *Journal of Dairy Science*, 92(10): 5199-5211.

Dall-Orsoletta, A.C., Oziemblowski, M.M., Berndt, A., Ribeiro-Filho, H.M.N. (2019). Enteric methane emission from grazing dairy cows receiving corn silage or ground corn supplementation. *Animal Feed Science and Technology*, 253: 65-73.

Dempster, A.P., Laird, N.M., Rubin, D.B. (1977). Maximum likelihood from incomplete data via the EM algorithm. *Journal of the royal statistical society: series B (methodological)*, 39(1): 1-22.

Doreau, M., Martin, C., Morgavi, D. (2017). Réduire les émissions de méthane entérique par l'alimentation des ruminants. *La revue française de la recherche en viandes et produits carnés*, 33: 2-7.

Dou, Z., Galligan, D.T., Ramberg Jr, C.F., Meadows, C., Ferguson, J.D. (2001). A survey of dairy farming in Pennsylvania: Nutrient management practices and implications. *Journal of Dairy Science*, 84(4): 966-973.

Dutreuil, M., Wattiaux, M., Hardie, C.A., Cabrera, V.E. (2014). Feeding strategies and manure management for cost-effective mitigation of greenhouse gas emissions from dairy farms in Wisconsin. *Journal of dairy science*, 97(9): 5904-5917.

Engel, S. (2016). The devil in the detail: a practical guide on designing payments for environmental services. *International Review of Environmental and Resource Economics*, 9(1-2): 131-177.

Hanrahan, L., McHugh, N., Hennessy, T., Moran, B., Kearney, R., Wallace, M., Shalloo, L. (2018). Factors associated with profitability in pasture-based systems of milk production. *Journal of dairy science*, 101(6): 5474-5485.

Hawkins, J., Weersink, A., Wagner-Riddle, C., Fox, G. (2015). Optimizing ration formulation as a strategy for greenhouse gas mitigation in intensive dairy production systems. *Agricultural Systems*, 137: 1-11.

Helming, J., Oskam, A., Thijssen, G. (1993). A micro-economic analysis of dairy farming in the Netherlands. *European Review of Agricultural Economics*, 20(3): 343-363.

Henry de Frahan, B., Baudry, A., De Blander, R., Polomé, P., Howitt, R. (2011). Dairy farms without quotas in Belgium: estimation and simulation with a flexible cost function. *European Review of Agricultural Economics*, 38(4): 469-495.

Henriksson, M., Flysjö, A., Cederberg, C., Swensson, C. (2011). Variation in carbon footprint of milk due to management differences between Swedish dairy farms. *Animal*, 5(9): 1474-1484.

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

Jarrige, R. (1989). *Ruminant nutrition: recommended allowances and feed tables*. John Libbey Eurotext, 389 p.

Koutchadé, O.P., Carpentier, A., Femenia, F. (2018). Modeling heterogeneous farm responses to European Union biofuel support with a random parameter multicrop model. *American Journal of Agricultural Economics*, 100(2): 434-455.

Leng, R. A. (1993). Quantitative ruminant nutrition—a green science. *Australian Journal of Agricultural Research*, 44(3): 363-380.

McLachlan, G.J., Lee, S.X., Rathnayake, S.I. (2019). Finite mixture models. *Annual review of statistics and its application*, 6: 355-378.

Marette, S., Millet, G. (2014). Economic benefits from promoting linseed in the diet of dairy cows for reducing methane emissions and improving milk quality. *Food Policy*, 46: 140-149.

Martin, C., Rouel, J., Jouany, J.P., Doreau, M., Chilliard, Y. (2008). Methane output and diet digestibility in response to feeding dairy cows crude linseed, extruded linseed, or linseed oil. *Journal of animal science*, 86(10): 2642-2650.

Martin, B., Lerch, S., Ferlay, A., Verdier-Metz, I., Cornu, A., Montel, M.C., Pradel, P. (2009). Extruded linseed and antioxidant supplementation of dairy cows diets: What are the influences on the milk and cheese sensory quality? *9th International meeting on mountain cheeses. INRA. Sainte-Eulalie*. 9: 14-15.

Martin, C., Morgavi, D.P., Doreau, M. (2010). Methane mitigation in ruminants: from microbe to the farm scale. *Animal*, 4(3): 351-365.

Nguyen, T.T.H., Van der Werf, H.M. G., Eugène, M., Veysset, P., Devun, J., Chesneau, G., Doreau, M. (2012). Effects of type of ration and allocation methods on the environmental impacts of beef-production systems. *Livestock Science*, 145(1-3): 239-251.

Renner, S., Sauer, J., El Benni, N. (2021). Why considering technological heterogeneity is important for evaluating farm performance? *European Review of Agricultural Economics*, 48(2): 415-445.

Samson, G.S., Gardebroek, C., Jongeneel, R.A. (2017). Analysing trade-offs between milk, feed and manure production on Dutch dairy farms. *European Review of Agricultural Economics*, 44(3): 475-498.

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

Sauvant, D., Giger-Reverdin, S., Serment, A., Broudiscou, L. (2011). Influences of diet and rumen fermentation on methane production by ruminants. *INRA Productions Animales*, 24(5): 433-446.

Thorup, V.M., Edwards, D., Friggens, N.C. (2012). On-farm estimation of energy balance in dairy cows using only frequent body weight measurements and body condition score. *Journal of dairy science*, 95(4): 1784-1793.

Van Middelaar, C.E., Dijkstra, J., Berentsen, P.B.M., De Boer, I.J.M. (2014). Cost-effectiveness of feeding strategies to reduce greenhouse gas emissions from dairy farming. *Journal of Dairy Science*, 97(4): 2427-2439.

Vellinga, T.V., Hoving, I.E. (2011). Maize silage for dairy cows: mitigation of methane emissions can be offset by land use change. *Nutrient cycling in agroecosystems*, 89(3): 413-426.

Weill, P., Kerhoas, N., Chesneau, G., Schmitt, B., Legrand, P., Rennaud, J.P. (2008). "Existe-t-il un lien entre production de méthane par les vaches laitières et profil en acides gras des laits ?" *Nutrition Clinique et Métabolisme*, 22(Suppl 1): S71-S72.

Weill, P., Chesneau G, Chilliard, Y, Doreau, M., Martin, C. (2009). Method for evaluating the quantity of methane produced by a dairy ruminant and method for decreasing and controlling such quantity, Patent priority France 0854230 of June 25, 2008 and PCT/EP 2009/057919 of June 24.

Weller, R.F., Bowling, P.J. (2007). The importance of nutrient balance, cropping strategy and quality of dairy cow diets in sustainable organic systems. *Journal of the Science of Food and Agriculture*, 87(15): 2768-2773.

White, B., Hanley, N. (2016). Should we pay for ecosystem service outputs, inputs or both? *Environmental and Resource Economics*, 63: 765-787.

Les **Working Papers SMART** sont produits par l'UMR SMART

- **UMR SMART**

L'Unité Mixte de Recherche (UMR 1302) *Structures et Marchés Agricoles, Ressources et Territoires* comprend les unités de recherche en Economie INRAE de Rennes et de Nantes et les unités pédagogiques du département Economie, Gestion et Société de L'Institut Agro Rennes-Angers.

Adresse:
UMR SMART, 4 allée Adolphe Bobierre, CS 61103, 35011 Rennes cedex

Site internet : https://www6.rennes.inrae.fr/smart

Liste complète des Working Papers SMART :
https://www6.rennes.inrae.fr/smart/Working-Papers
https://ideas.repec.org/s/rae/wpaper.html
http://ageconsearch.umn.edu/handle/204962/

The **Working Papers SMART** are produced by UMR SMART

- **UMR SMART**

The Mixed Research Unit (UMR1302) *Structures and Markets in Agriculture, Resources and Territories* is composed of the INRAE research units in Economics in Rennes and Nantes, and the Department of Economics, Management and Society of L'Institut Agro Rennes-Angers.

Address:
UMR SMART, 4 allée Adolphe Bobierre, CS 61103, 35011 Rennes cedex

Website: https://www6.rennes.inrae.fr/smart_eng/

Full list of the Working Papers SMART:
https://www6.rennes.inrae.fr/smart/Working-Papers
https://ideas.repec.org/s/rae/wpaper.html
https://ageconsearch.umn.edu/search?cc=913&ln=en&c=913

Contact

Working Papers SMART
INRAE, UMR SMART
4 allée Adolphe Bobierre, CS 61103
35011 Rennes cedex, France
Email : smart-wp@inrae.fr

2023

Working Papers SMART

UMR **SMART** (Structures et Marchés Agricoles, Ressources et Territoires)

INRAE et l'Institut Agro Rennes-Angers, France