Organic farming offers promising mitigation potential in dairy systems without compromising economic performances

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Abstract

There is a lack of clear empirical evidence towards the lower carbon footprint of organic food products, in particular in the dairy sector. Until now, small sample sizes, lack of properly defined counterfactual and the omission of land-use related emissions have hindered comparisons of organic and conventional products. Here we bridge these gaps by mobilizing a uniquely large dataset of 3,074 French dairy farms. Using propensity score weighting, we find that the carbon footprint of organic milk is 19% (95%*CI* = [10% - 28%]) lower than its conventional counterpart without indirect land-use change and 11% (95%*CI* = [5% - 17%]) lower with indirect land use changes. In both production systems, farms' profitability is similar. We simulate the consequences of the *Green deal* target of 25% of agricultural land devoted to organic dairy farming and show that this policy would reduce the greenhouse gas emissions of the French dairy sector by 9.01 to 9.64%.

Keywords: organic farming; greenhouse gas emissions; gross margin; dairy farms; land use changes; Green Deal.

1. Introduction

Promoting extensive farming systems, and in particular organic farming, has been presented as a sustainable way of limiting greenhouse gases emissions (GHGE) and other environmental externalities in public policies, such as the European Union's "Farm to Fork Strategy" (European Commission 2020) or the 2014-2020 Common Agricultural Policy which offered subsidies to farmers who convert or maintain organic farming. Indeed, organic farming systems do not use chemical inputs (fertilizers, pesticides, …) which are responsible for biodiversity loss, water eutrophication and nitrous oxide emissions (Mäder et al. 2002; Reganold et Wachter 2016). However, lower average yields in organic systems (Seufert, Ramankutty, et Foley 2012) tend to offset the climate benefits of lower inputs use when they are expressed on per-unit-of-product basis (Bellassen et al. 2021). Moreover, lower productivity in such systems can lead to indirect land-use changes through agricultural intensification elsewhere and/or expansion of agricultural land with negative consequences on emissions (Smith et al. 2019).

Recently, the EU has confirmed its inclination toward organic farming as a part of its *Green Deal*, with a stated objective of 25% of the EU's agricultural land devoted to organic farming by 2030 (« Communication from the commission on an action plan for the development of organic production » 2021). Having in mind the above-cited trade-off between the productivity of the dairy sector and its GHGE, legitimate interrogations arise concerning the feasibility of such policy, the extent of the overall milk production decrease, the economic consequences for farmers and the effective reduction of the GHGE in the sector. This paper provides some answers to these questions by mobilizing a unique data set of 3,054 Life Cycle Assessments of organic and conventional dairy farms in France, modelling land-use and management changes (LUC) impacts on GHGE and estimating economics performances of farming systems. However, we do not account for price effects and let this important issue opened for further research.

To investigate the potential for climate change mitigation of the *Green Deal*'s target of 25% of organic land in the EU, clear and thorough assessments of the GHGE of organic farming - especially in comparison to conventional farming systems - are needed. The stakes are particularly high for the livestock sector which accounts for 14-24% of global GHGE and for almost 80% of the GHGE from the global agricultural sector, when LUC are accounted for (Rogissart, Foucherot, et Bellassen 2019). In France specifically, farm emissions (excluding land-use changes) from the livestock sector are estimated at around 19% of the territorial GHGE emissions (Ministère de la Transition Ecologique et Solidaire 2020).

Two strands of the scientific literature have been attempting to assess the environmental performance of organic farming. Firstly, bottom-up life cycle assessments (LCA) have been used to compare the carbon footprint of actual farms, both organic and conventional, with conflicting results (Cederberg et Mattsson 2000; Kristensen et al. 2011; Stonehouse, Clark, et Ogini 2001; Thomassen et al. 2008; van der Werf, Kanyarushoki, et Corson 2009; Bellassen et al. 2021; Haas, Wetterich, et Köpke 2001). Three important pitfalls hinder the formulation of a clear conclusion from LCAs:

- they rely on small sample sizes, ranging from 2 to 81 farms for those involving dairy farms (A.6). Meta-analysis, the typical tool to overcome small sample sizes in individual studies, also came up with conflicting results (Tuomisto et al. 2012; Mondelaers, Aertsens, et Van Huylenbroeck

2009; Clark et Tilman 2017) or refuse to conclude due to the heterogeneity in methods and perimeter between LCA studies (Meier et al. 2015);

- the choice of counterfactual conventional farms is usually not explicit in existing studies. This is likely to result in misleading comparisons of organic vs. conventional farms' performances, as the influence of organic practices is mixed with differences in farms' structure and pedo-climatic conditions that translate into self-selection bias (Froehlich, Melo, et Sampaio 2018);
- they do not account for emissions from direct and indirect land-use and management changes, which are estimated at 11-34% of the carbon footprint of the livestock sector (Rogissart, Foucherot, et Bellassen 2019).

Secondly, top-down large-scale modelling of the agricultural sector, such as computable general equilibrium or global land use models, have shown that developing organic farming to a large scale would increase global GHGE due to indirect land-use changes (Bellora et Bureau 2016; Muller et al. 2017; Smith et al. 2019). However, these approaches have neglected direct land-use and management changes – such as conversion of maize fields into grasslands or planting of hedges – that may offset indirect land-use changes. Moreover, these models rely on many assumptions and interactions that are difficult to validate and cannot integrate the heterogeneity of farming practices and the specificities of key agricultural products.

Here we address the three important pitfalls of existing LCAs. Our dataset gathers 3,054 LCAs of dairy farms in France – that is almost 40 times more the largest dataset used in past studies – among which 72 are organic. Such a large sample size in conventional farms allows to properly and objectively select conventional counterfactuals for organic farms through propensity score weighting and thereby strengthens causal inferences on the differences found between organic and conventional farms' performances. Indeed, most comparisons of environmental and, to a lesser extent, economic performances of organic farming do not control for the self-selection of organic farms and the potential structural differences between organic and conventional farms (Mayen, Balagtas, et Alexander 2010). Moreover, as we are able to select credible counterfactuals, we can simulate the potential impacts of the EU's objective of 25% of its agricultural land devoted to organic farming by 2030. GHGE originating from direct and indirect land use and management changes are estimated through a model of land use and management at the farm scale, inspired by Searchinger et al. (2018) and Lambotte et al. (2021). Ultimately, the difference in milk's carbon footprint between organic and conventional farms is assessed with average treatment effects on the treated (ATTs) of several GHGE estimates. We demonstrate that the carbon footprint of organic milk is 19% (95%*CI* = [10% – 28%]) lower than its conventional counterpart without indirect land-use change and 11% (95%*CI* = [5% – 17%]) lower with indirect land use changes.

In addition, we estimate the difference in economic performance between organic and conventional farms, measured by their gross operating margins. Adding an economic dimension to the comparison of the environmental performances of organic and conventional farming systems is essential as such changes in farming practices will not be adopted if they threaten the economic viability of the farms (Dessart, Barreiro-Hurlé, et van Bavel 2019). The literature on the economic performances of organic and conventional farms is also substantial. Crowder and Reganold (2015) reviews 129 studies that compare the economic performance of organic and conventional farming, and finds that due to the price premium, organic farms were 22 to 35% more profitable. More specific to dairy farming, the Farm Accountancy Data Network (FADN) has been mobilized to prove that organic dairy farming has higher revenue per liter of milk produced as well as lower production costs (European Commission 2013; Flubacher, Sheldon, et Müller 2015; Sanders et al. 2016) and higher gross margin per cow (Grovermann et al. 2021).

Interestingly, matching and related methods are more commonly used in the literature on the economic performances of the organic and conventional farming systems, compared to the literature on the environmental performances. Self-selection in organic farming systems is thus accounted for example in studies on organic and conventional dairy farming in Switzerland (Flubacher, Sheldon, et Müller 2015), in Norway (Hansen, Haga, et Lindblad 2021) or beef production in the US (Gillespie et Nehring 2013). In this study, using propensity score weighting and a large dataset, we find that once controlling for self-selection in organic farming, gross margins are not significantly different between organic and conventional farms and thus that organic dairy farming reduces the carbon footprint of milk without compromising farms' economic performances.

Lastly, we simulate the environmental consequences in the dairy production sector of the EU *Green deal* objective of 25% of agricultural land devoted to organic farming. With the example of France, which represented 16% of the EU milk production in 2015 (Chatellier 2017), we show that the massive organic conversions necessary to reach the targeted 25% of organic land would result in a 9.01 to 9.64% reduction in the GHGE of the French agricultural sector. More precisely, the *Green deal* would lead to a 7.40% decrease of French milk production and a substitution of 14.68% of its current conventional milk production by organic milk.

2. Methods

2.1. Population characterization and notations

Consider a population of N_i farms (indexed by $i = 1 \dots N$). Each farm is characterized by a matrix of outputs O_i (e.g., liters of milk produced (M_i), cereals and cows sold…) produced by combining two quasi-fixed inputs, land (A_i) and herd size, and a matrix of variable inputs X_i (e.g. fertilizer, concentrates, fuel, annual work units (AWU), …).

Denote by Π_i the gross margin, defined as $\Pi_i = p_i^O * O_i - p_i^X * X_i$ where p_i^O is a vector of output prices and p_i^X a vector of input prices. We refer the reader to the online supplementary material – section 1 (SM.1) for more details.

Moreover, each farm emits an amount E_i of GHG as a co-product of its production activity. As conversions of cropland <–> pastures results in soil carbon changes, and thereby GHGE or carbon storage, each farm is considered to emit or store an amount C_i^{dLUC} of carbon based on its share of permanent grassland compared to a reference farm (set at the average share of permanent grassland in the dataset without loss of generality). Similarly, three farming practices relevant to dairy farms have been shown to store carbon: planting hedges, increasing the share of temporary grassland in crop rotations and increasing the total nitrogen fertilization – mineral and organic – of grasslands. Thus, each farm is considered to emit or store an amount C_i^{Pr} based on its implementation of these practices compared to a reference farm. Finally, some farms import cows' feed from other farms or countries, which involves indirect land use changes (iLUC, see 2.2.). In this case, we obtain a new component of farm emissions, C_i^{iLUC}. As a results, the net carbon footprint of farms and their produces, $E_i + C_i^{dLUC} + C_i^{Pr} + C_i^{iLUC}$, can be decomposed between their gross carbon footprint E_i and the land-use and management related emissions or storage, $C_i^{dLUC} + C_i^{Pr}$or $C_i^{dLUC} + C_i^{Pr} + C_i^{iLUC}$, depending on whether one deems that it is legitimate to account for indirect land-use changes.

To measure the economic performance, we mainly consider the gross margin (*Gross Margin*) per annual work unit $\frac{\Pi_i}{AWU_i}$, per ha, $\frac{\Pi_i}{Ha_i}$ or per liter of milk produced, $\frac{\Pi_i}{M_i}$. As indicators of the environmental performance we use the 4 GHG emission estimates, harmonized per liter (fat-and-protein corrected) of milk produced, $\frac{E_i}{M_i}, \frac{E_i+C_i^{dLUC}}{M_i}, \frac{E_i+C_i^{dLUC}+C_i^{Pr.}}{M_i}, \frac{E_i+C_i^{dLUC}+C_i^{iLUC}+C_i^{Pr.}}{M_i}$, which we name *Gross GHGE, dLUC GHGE, dLUC + Practices GHGE* and *dLUC + iLUC + Practices GHGE* respectively.

2.2. Estimation of the environmental performance.

Gross GHGE. To assess the environmental performance of farms, we focus on GHGE for two reasons: first because climate change is arguably the most pressing environmental challenge of the 21st century and second because GHGE are correlated with many other environmental impacts such as eutrophication, acidification and energy use (Guerci et al. 2013). Gross GHG emissions E_i – without carbon emissions/sequestration related to land use and management – are computed using CAP'2ER, a GHGE calculator developed by the *Institut de l'Elevage* and following LCA guidelines (Institut de L'Elevage 2013). However, contrary to the energetic allocation of

CAP'2ER, we implemented a more conventional economic allocation whereby the GHG balance of the farm is allocated to the three outputs of farms – milk, meat and cash crops – in proportion of the share of each product type in farm revenues (Baldini, Gardoni, et Guarino 2017). The system boundaries are "cradle-to-farm gate", including enteric digestion, manure management, fertilizers, fuel and energy use, but also the GHG emissions due to the production and transportation of concentrate feed and fertilizers. Details on the estimation of LUC-related GHGE are provided in SM.2 but a summary of the model is presented below.

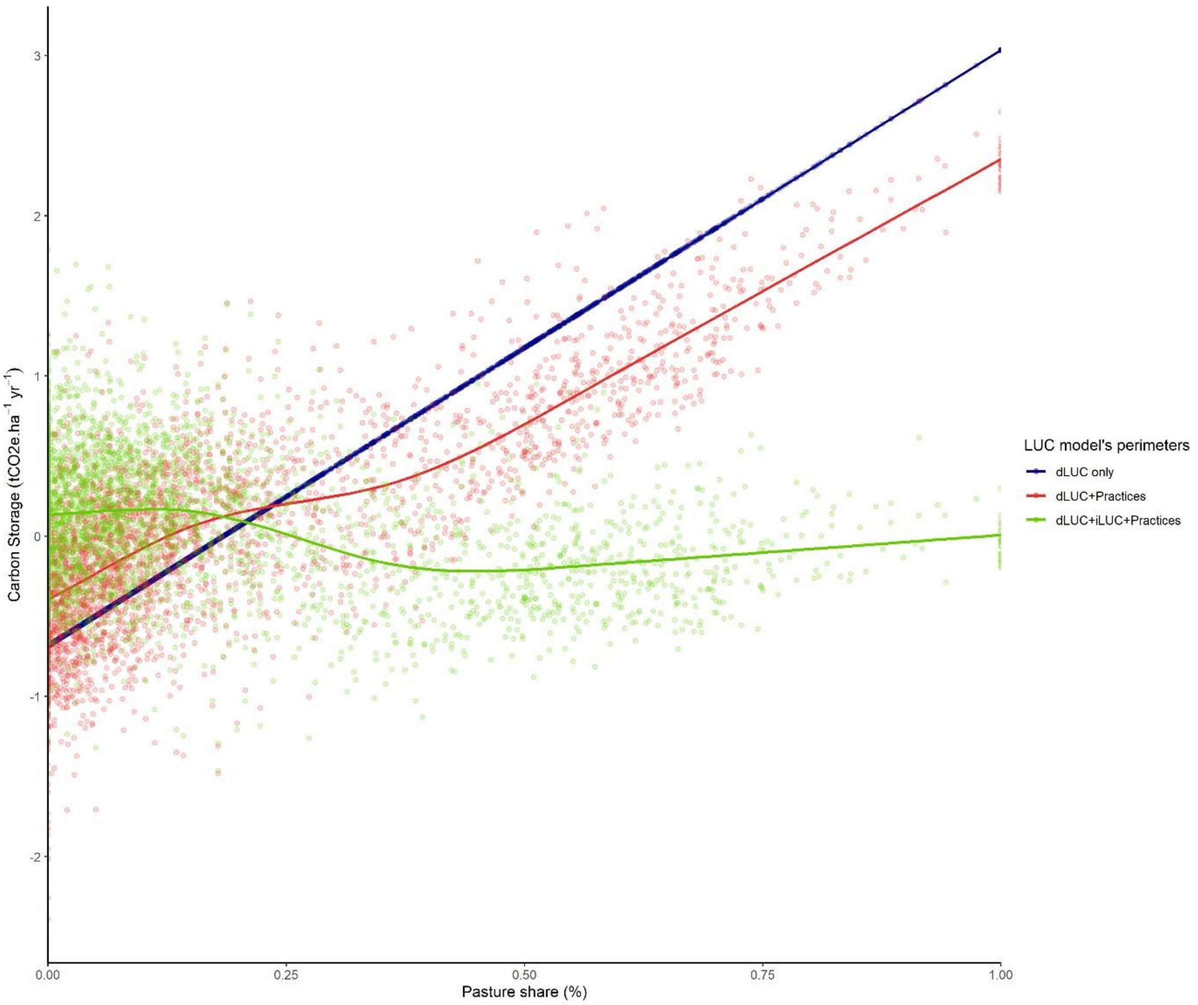
Direct LUC. The land use of each farm in our dataset is compared to a reference farm. We then estimate the carbon fluxes that are being avoided by the choice of each farm to maintain its observed land use rather than transitioning towards the land use of the reference farm. The land use shares in our reference farm is set to the sample average (18% permanent pastures, 82% of cropland and temporary grassland). The above estimate is akin to direct LUC (dLUC) as defined by Herrero et al. (2013). Note that the choice of the reference farm does not affect our results on the relative difference in GHGE between farms within the sample. The difference in carbon stocks between two land uses is assumed to be emitted or stored linearly over a transition *period* as in IPCC (2019). The reference stock for each land use sums its current stock and the discounted sum its expected change over the foreseeable future as estimated by EFESE (2019). For example, a farm that has 100% of pasture and 100 ha of total land is estimated to sequester 3.72 tCO2e.ha^{-1} yr^{-1} on the 82 ha which would have been converted to cropland to match the reference farm (Figure 1). The impact of temporary grassland on soil carbon is considered within farming practices (see below). The actual values and their sources are detailed in SM.2.

The impacts of key farming practices on biomass and soil carbon are also estimated in a similar fashion. Based on a recent review in France (Pellerin, Bamière, et Launay 2019), we identify three key practices that are relevant in dairy farming and that change biomass and soil carbon stocks: the share of temporary grasslands in crops rotation, the amount of nitrogen (mineral or organic) fertilization in pastures and the amount of hedges. The carbon impact of these practices follows a temporal pattern similar to the carbon impact of dLUC (Figure 1): a change in practice leads to carbon sequestration or emissions that saturate over time as soil and biomass carbon reach a new steady-state equilibrium. Similar to our dLUC model, only the differences from the reference farm are considered.

Indirect LUC (iLUC) is a more controversial topic and its estimates are laden with high uncertainties. 82 ha of pasture do not yield as much nutritious capacity as 82 ha of cropland. As a result such a land-use change, either milk production will decrease or animals will require a complement in concentrates. The latter rationale is easier to simulate and we therefore base of our method to estimate iLUC on this assumption: a virtual quantity of concentrates is assumed to be added or subtracted to the actual quantity of concentrates fed to the cows in order to reach the nutritious capacity that the observed farm would have if its share of permanent grassland was the same as the reference farm. We include as iLUC the area that is deforested in Brazil to meet the demand of soybean cakes of the observed farm (see SM.2 for details on the estimation of the deforested area). This iLUC estimation is akin to the index of the efficiency of land use changes developed by Searchinger et al. (2018), which accounts for the global efficiency of food production and carbon storage of each hectare of land, comparing its nutritive capacity and its carbon storage capacity to other land uses. Our iLUC estimates only considers the lower yield related to the difference in grassland share between farms. The potential iLUC related to the lower yield of organic forage and, therefore, to the lower productivity in liters per hectare of organic farms is not considered. Our implicit assumption is therefore that French demand for milk is fully elastic and will adjust perfectly to a reduced domestic supply. To the contrary, Smith et al. (2019) implicitly assume that British food demand is totally inelastic and will not change despite major changes in domestic supply. The truth is likely in between but current empirical evidence leans towards elastic demand: people eating more organic food consume less animal products, and so much less that their diet has a lower than average carbon footprint (Treu et al. 2017; Lacour et al. 2018; Baudry et al. 2019).

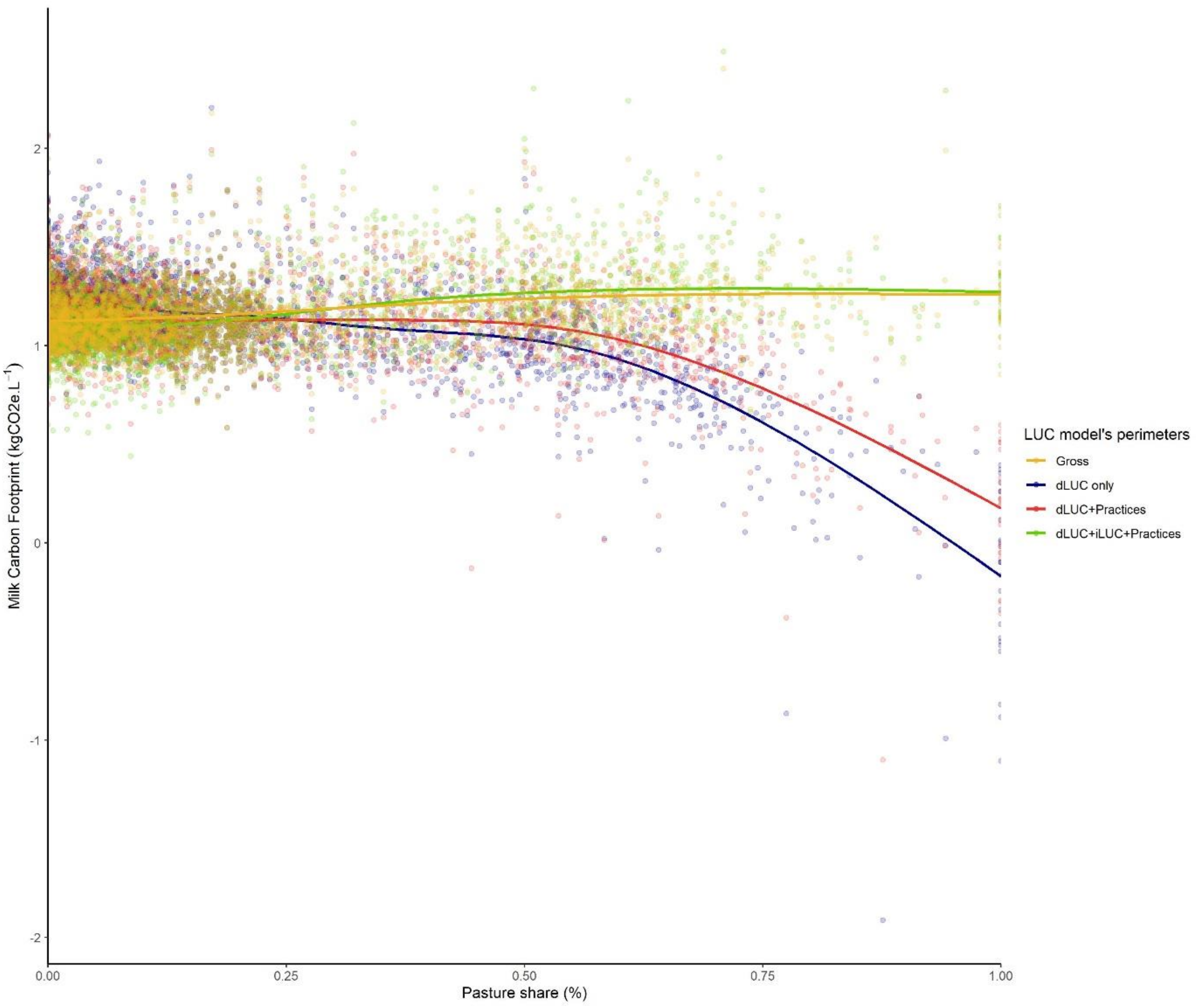
Figure 1 summarizes the role of the key variable of our LUC model, the share of permanent pasture in the farms' land uses, on carbon sequestration. In our model, carbon storage from dLUC is a linear and positive function of the share of pasture (blue line in Figure 1). However, including management practices (red line in Figure 1) results in a lower carbon sequestration for the most extensive farms, i.e. the farms with the largest share of pasture. Indeed, a high share of pasture naturally results in a lower share of temporary pasture, whose carbon storage is accounted for in the *practices* perimeter. Lastly, accounting for iLUC (green line in Figure 1) renders the total carbon sequestration null, or even negative for the most extensive farms in our sample, as the modeling approach positively relates iLUC and the share of pastures through the compensating use of concentrates for less productive farms.

Figure 1 Non-linear fit of carbon storage for the three perimeters considered in the LUC model (dLUC, dLUC + practices and dLUC + practices + iLUC).



Similarly, Figure 2 presents the effect of the share of pasture in the land use of farms on the carbon footprint of their milk. In comparison to the gross carbon footprint of the farms (orange line in Figure 2), including dLUC reduces the carbon footprint of milk, especially for milk produced on extensive farms. Similarly, adding the impact of *practices* reduces on-farm carbon sequestration on the most extensive farms (Figure 1) and thus relatively increases milk's carbon footprint. Interestingly, accounting for iLUC cancels out the effect of dLUC and practices, making the gross carbon footprint and the dLUC+iLUC+Practices carbon footprint almost identical for a given share of pasture.

Figure 2 Non-linear fit of milk's carbon footprint for the three perimeters considered in the LUC model (dLUC, dLUC + practices and dLUC + practices + iLUC)



2.3. Regression adjusted propensity score weighting estimator of the average treatment effect on the treated

Our estimator of the average treatment effect on the organic farms (the *treated*) on several performance indicators is built on a doubly robust procedure to account for selection bias in the treated observations and possible cofounders of the farms' performances and their production technology. In a first instance, we estimate the farms' probability to choose the organic production technology (*propensity scores*) based on several structural and pedo-climatic covariates. Using the estimated propensity scores, we assign weights to each observation and perform weighted regressions, using the inverse of the propensity scores as weights and controlling for remaining differences in the covariates.

Firstly, the proper counterfactuals of the organic farms in our dataset is estimated through a propensity score weighting (PSW) model. This model is estimated in two steps: the probability of receiving the treatment – the propensity score – (here, the probability that a farm chooses an organic production technology), is estimated for each farm using the selected covariates and then the farms are weighted based on the estimated propensity scores.

Let $\pi(X)$ be the propensity score such as $\pi(X) = \mathbb{E}[T|X] = Pr(T = 1|X)$ where T is the treatment indicator ($T \in \mathcal{T} = \{0,1\}$, e.g. conventional or organic production technology) and X is the matrix of controlling covariates. The propensity score model is described as $\pi(X, \alpha)$ and includes as covariates X the number and breed of the cows, the acreage of the farm, the administrative region of the farms, the specialization of the farms (dairy, crops, diversified), the slope, the rainfall, the temperature and pedological characteristics. These covariates are selected based on other applications of matching procedures in the comparison of organic and conventional livestock farms' performances (Kirchweger, Kantelhardt, et Leisch 2016; Gillespie et Nehring 2013; Mayen, Balagtas, et Alexander 2010; Hansen, Haga, et Lindblad 2021; Flubacher, Sheldon, et Müller 2015) and on the potential influence they may have on the propensity to self-select an organic production technology. Indeed, this literature shows that organic farms tend to be more extensive, more often in mountainous area, with a poorer soil or more diversified, which may affect the environmental and economic performances, prior to receiving the treatment, as well as their probability to receive the treatment. Other farm characteristics such as the age and educational level of the manager are well known to affect the probability to adopt organic farming (Läpple et Kelley 2015; Schmidtner et al. 2011; Latruffe et Nauges 2014) but were not available in our dataset. Weights $w(X)$ are computed based on the estimated propensity scores and assigned to each farm such that $w(X) = T + \frac{\pi(X)}{1-\pi(X)}(1 - T)$, the propensity score weighting thus assures that the distribution of the covariates in the treated and control individuals' subsamples is similar. The average treatment effect on the total population (ATE) can be obtained using different weights $w^{ATE}(X) = T * \frac{1}{\pi(X)} + \frac{1}{1-\pi(X)}(1 - T)$, which is generally named inverse propensity score weighting, as the weights are inversely related to the propensity score. While the ATT estimates the average effect of selecting an organic production technology for the organic farms only, the ATE estimates the average effect for both the organic and conventional farms and may be biased if structural differences or self-selection affect treatment assignment.

Secondly, weighted regressions of the outcomes of interest on the treatment indicator and the covariates of the propensity score model are used the average treatment effect on the treated farms (ATT). The formal definition of the ATT, $\tau(X)$, is:

$\tau(X) = \mathbb{E}[\tau(X)|T = 1, X] = \mathbb{E}[Y(1) - Y(0)|T = 1, X] = \mathbb{E}[Y(1)|T = 1, X] - \mathbb{E}[Y(0)|T = 1, X]$, where $Y(1)$ is the potential outcome under the treatment and $Y(0)$ is the potential outcome without the treatment. More formally, we set $Y_i = \begin{cases} Y_i(1) & if\ T_i = 1 \\ Y_i(0) & if\ T_i = 0 \end{cases}$, $\mathbb{E}[Y(1)] = \mathbb{E}[T_i Y_i]$ and $\mathbb{E}[Y(0)] = \mathbb{E}[(1 - T_i)Y_i]$. This formulation of the ATT illustrate the main purpose of propensity score weighting: as we do not observe farms transitioning from conventional to organic production technologies, we do not observe $\mathbb{E}[Y(0)|T = 1, X]$. The propensity score weighting model estimates the counterfactual $\mathbb{E}[Y(0)|T = 1, X]$ using the information from all the control units, i.e. all the conventional farms while weighting them to ensure that the conventional farms that are the closest to the organic farms in terms of control covariates weight more in the estimation of the ATT. Doing so, the weighted conventional farms' subsample is as close as possible to the organic farms' subsample while avoiding the loss of information via the non-pairing of some farms in matching methods, especially in cases of highly unequal sample sized for control and treated groups. The estimator from the propensity score weighting model is $\tau^{PSW} = \frac{1}{\sum_i T_i}\sum_i \left(T_i Y_i - \frac{\pi(X_i,\hat{\alpha})(1-T_i)}{1-\pi(X_i,\hat{\alpha})} Y_i\right)$, which is the weighted average of $\tau(X) = [Y(1) - Y(0)|T = 1, X]$, with weights given by $\hat{w}(X)$ and can be directly estimated by a weighted regression $Y = \alpha + \tau^{PSW} T_i$, where α captures the counterfactual's average outcome.

The estimator proposed here is an augmented version of τ^{PSW} with pooled regression adjustment, τ_{PRA}^{PSW} (Abadie et Imbens 2011; Negi et Wooldridge 2021). Regression adjustment reduces the bias from τ^{PSW} if the propensity score model $\pi(X, \alpha)$ is not consistent. Indeed, in that case, balance of the covariates between the treated and outcomes subsamples is not achieved and the estimator τ_{Adj}^{PSW} is augmented with the covariates to account for remaining difference between treated and control subsamples. Alternative versions of this estimator exist in the literature, especially including interactions between the treatment indicator and the covariates in specific cases where the slopes of the linear projections of the outcome on the covariates differ between treated and control samples. This estimator is often used in empirical analysis (Bishop, Leite, et Snyder 2018; Kang et Schafer 2007) as it is doubly robust and can be easily estimated with a weighted regression $Y = \alpha + \tau_{Adj}^{PSW} T_i + \beta X$ with weights $\hat{w}(X)$ from a propensity score model. For completeness, we also estimate τ_{Adj} which is an ordinary least squares of $Y = \alpha + \tau_{Adj} T_i + \beta X$, i.e. without propensity score weighting. If both τ_{Adj} and τ^{PSW} are close, τ_{Adj}^{PSW} is doubly robust, while if τ_{Adj} and τ^{PSW} differ and only one is consistent, τ_{Adj}^{PSW} is simply robust. If neither τ_{Adj} nor τ^{PSW} is consistent, then τ_{Adj}^{PSW} is likely inconsistent but less biased.

To guarantee that the propensity score model is correct as correctly specified as possible and thus that the doubly robust estimator is unbiased we estimate the propensity score model $\pi(X, \alpha)$ via generalized boosted regression instead of classical logit regression as it handles better non-linearity, skewed distribution and outliers and implement all possible two-way interactions between the covariates. This is highly relevant with our data as the sizes of our groups strongly differ and the farms, sampled from the whole of France, are very diverse, with implies possible non-linearity and outliers. In addition, generalized boosted models are machine-learning algorithms, which stimulate a large number of decision trees (we use 3,000 trees in our estimations) using a random sample of the data for each tree. The data that was poorly modeled in a given tree has a higher probability of being selected by the following tree, which uses the information from the previous trees to increase the accuracy of the estimation, until a maximal accuracy is achieved (Ridgeway 2020).

We estimate our doubly robust estimator of the ATT of organic farming on the set of GHGE and gross margin indicators of organic farms compared to their conventional counterparts. One can assess the efficacy of the propensity score weighting by comparing the average differences between the covariates in organic farms and their counterparts before and after the procedure (Figure A.2a). Without a matching procedure, organic have more agricultural land and higher slope, more rainfall and a poorer soil compare to conventional farms. After the propensity score weighting, these differences are resorbed, which supports the assumption of conditional independence of the treatment ($T \perp Y(0)| X$) and the propensity score distribution is more homogenous among the organic farms and their counterfactuals (Figure A.2ab). Thus, the common support assumption (i.e. $\pi(X) < 1$) is confirmed and we observe enough conventional farms that are structurally similar to organic farms to perform the ATT simulation and the simulation of the *Green Deal* target of 25% of organic land by 2030. Finally, we perform further sensitivity analyses of the propensity scores weighting model and of the ATT estimator that we discuss in section 4.

3. Data

Our main data source are the life cycle inventories of 3,074 dairy farms in France, once misreported values have been filtered out (Supplementary Information 1). Each farm is surveyed only once, in either 2013 (74%), 2014 (25%) or 2015 (1%) and may be located in any French region (a map of the farms localizations at the commune level is available in SM 3). These inventories gather all the necessary technical and managerial information that is used to compute GHGE via CAP'2ER. They also provide detailed information on farmers' practices and farms' characteristics, such as farm's and herd's sizes, the amount of concentrate feed used, the cereals produced and used on-farm, the fertilizers or labor uses. A summary description of the dataset is provided in Table 1, while the descriptive statistics and the definition of the covariates and outcomes used in the propensity score weighting model and the ATT estimator are available in Table A.1. The agricultural census is an exhaustive census of all French farms and allows us to compare our sample to the whole population of French dairy farms. Both the life cycle inventories and the agricultural census are annual data, so that we do not have seasonality effects in our analysis.

Table 1. Summary description of the data

Production Mode	Productivity per cow (L.lactating cow^{-1}.yr^{-1})	Productivity per ha (L.ha^{-1})	Herd size (livestock unit)	Farm acreage (ha)	Milk Production (L.yr^{-1})	Farms in the sample
Conventional	7,039	7,607	87	62	439,686	2,982
Organic	5,069	3,650	93	95	330,046	72
Agricultural Census – Conventional	/	/	119	81	/	47,344
Agricultural Census – Organic	/	/	103	85	/	1,452

To estimate the gross margin Π_i of each farm, the physical flows gathered from the LCAs are multiplied by prices (see SM.1). The prices of most inputs and outputs are estimated using the FADN average for the corresponding year and NUTS2 region, with the following exceptions:

- The prices of fertilizers and concentrates, which cannot be derived directly from the FADN, are obtained from Eurostat (Eurostat 2018).
- The buying and selling prices of dairy cows, reformed cows and heifers is gathered from the *Cotation des gros bovins entrée abattoir (1993 - 2017)* of the French Ministry for Agriculture and Food.

To compute the GHGE related to land-use changes (C_i^{dLUC}, C_i^{Pr} & C_i^{iLUC}), we use our theoretical model introduced in section 2.2 and further detailed in SM.2.

4. Results and discussion

4.1. Organic farms emit less GHGE than their conventional counterfactuals when accounting farming practices and/or indirect land use changes

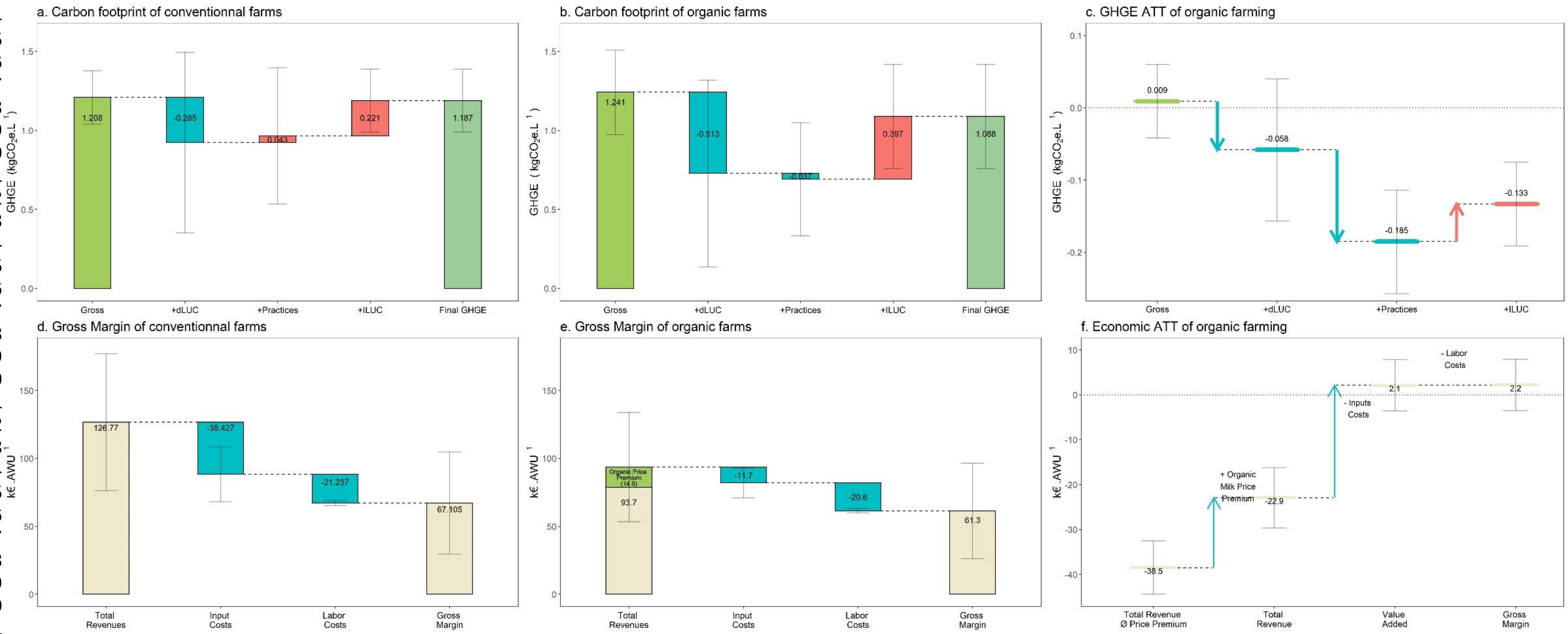
In our preferred definition of carbon footprint - including emissions from inputs, production and direct land use and management - the carbon footprint of organic milk is 19% (95%*CI* = [10% - 28%]) or 0.185 kgCO2e.L^{-1} (95%*CI* = [0.10 – 0.27]) lower than its conventional counterparts (Table 2, row 1 and A.5). Including indirect land-use change effects reduces the benefits of organic milk to 11% (95%*CI* = [5% - 17%]) or 0.133 kgCO2e.L^{-1} (95%*CI* = [0.06 – 0.20]). The results are robust to a range of different specifications of the regression adjusted propensity score weighting estimator τ_{Adj}^{PSW} including or excluding different control covariates, although some changes are worth noting (Table 2, rows 2 to 4). Indeed, including milk production as a matching variable greatly restrains the possibility to find counterfactuals to organic farms, as few conventional farms would have a similar production volume for an identical herd size and surface, i.e. a similar land and cow productivities. If one controls for the production volume, and thus indirectly for cow and land productivities, organic milk has a significantly lower gross carbon footprint than conventional milk and a significantly gross margin per annual work unit. The estimator that omits to adjust for the remaining difference in covariates between the organic farms and their weighted counterparts (Table 2, row 5) yields the expected results. Indeed, the ATT estimates are larger, i.e. biased upward as they do not fully control for the structural difference between the organic and conventional farms. The naive estimator of the treatment effects of organic farming that omit the propensity score weighting model and results in a simple ordinary least squares regression also provides upward biased estimates of the ATTs as the self-selection of organic farms is not accounted for (Table 2, row 6). However, prior to selecting the organic production technology, these farms were more likely to be already on the extensive spectrum of the dairy production, and without propensity score weighting or another matching procedure, the difference in outcomes between organic and conventional farms integrate these structural differences. Increasing the *transition period* over which the carbon storage or emissions from land-use changes happen from the IPCC default of 20 years (IPCC 2019) to an upper bound of 50 years (Poeplau et Don 2013) substantially attenuates the environmental benefits associated with organic farming. Indeed, with a 50 years transition period of organic milk to 6% (95%*CI* = [1% - 11%]) and 4% (95%*CI* = [-1% - 9%]) with indirect LUC (Table 2, row 7). Finally, estimating the average treatment effect (ATE) on the whole sample, not only on organic farms, shows close results to our main estimator (Table 2, row 8). As ATE and ATT estimates are theoretically equal when the distributions of the covariates and outcomes are identical in the treated and control subsamples, the additional result improves the robustness of our modelling approach. Finally, we present in A. a sensitivity analysis of the propensity score model, extending the idea behind Rosenbaum bounds to a propensity score weighting model (McCaffrey, Ridgeway, et Morral 2004). More specifically, we evaluate the presence of hidden bias, the presence of unobserved variables that would influence the probability of receiving the treatment and would thus violate the conditional indepence assuption (see Section 2 for further details). We find that our ATT estimates are robust to a large range of correlation between the outcomes and unobserved variables (Table SM.4). Comparison of the different GHGE estimates with previous studies are presented in SM 5. The correlation patterns between environmental and economic performances of both organic and conventional farming systems are also provided in SM 6.

Table 2. Average treatment effect on the performances of organic farms

Treatment effect estimator	Gross GHGE	dLUC GHGE	dLUC + Seq. Practices GHGE	dLUC + iLUC + Seq. Practices GHGE	dLUC + iLUC + Seq. Practices 2.5%	dLUC + iLUC + Seq. Practices 97.5%	Gross Margin per liter of milk	Gross Margin per hectare	Gross Margin per AWU	Gross Margin without price premium	Total Revenue	Value Added	Milk Production
	kgCO$_2$e.L^{-1}	kgCO$_2$e.L^{-1}	kgCO$_2$e.L^{-1}	kgCO$_2$e.L^{-1}	kgCO$_2$e.L^{-1}	kgCO$_2$e.L^{-1}	€.L^{-1}	€.Ha^{-1}	€.AWU^{-1}	€. AWU^{-1}	€. AWU^{-1}	€.AWU^{-1}	kL
τ_{Adj}^{PSW}	0.01 (0.03)	-0.06 (0.06)	-0.19*** (0.04)	-0.13*** (0.04)	-0.20*** (0.05)	-0.12*** (0.04)	0.12*** (0.01)	96.49* (55.28)	2,240.1 (3,463)	-13,300.7*** (2,954.9)	-22,934.1*** (4,090.6)	2,070.9 (3,462.5)	-111,078.7*** (11,226.4)
τ_{Adj}^{PSW} - with milk production	-0.14*** (0.03)	0.04 (0.09)	-0.11* (0.06)	-0.26*** (0.03)	-0.08 (0.08)	-0.29*** (0.05)	0.14*** (0.01)	358.11*** (55.69)	11,753.5*** (3,271.4)	-3,504 (2,931.4)	-8,104.6** (4,125.3)	11,679.4*** (3,302.2)	-75,212.9*** (12,878.1)
τ_{Adj}^{PSW} - without farms' surface	0.02 (0.03)	-0.14** (0.06)	-0.25*** (0.04)	-0.13*** (0.04)	-0.27*** (0.05)	-0.09** (0.04)	0.12*** (0.01)	-53.25 (67.41)	511.7 (3,435.6)	-14,669.9*** (2,960.3)	-25,763.4*** (4,120.5)	314.4 (3,437.3)	-112,188.8*** (10,942.7)
τ_{Adj}^{PSW} - without herd size	0.02 (0.03)	-0.11* (0.06)	-0.23*** (0.04)	-0.13*** (0.04)	-0.25*** (0.05)	-0.10** (0.05)	0.12*** (0.01)	-1.19 (67.40)	-1,091.9 (3,752.3)	-16,226.4*** (3,223.1)	-27,600.4*** (4,662)	-1,298.8 (3,756.2)	-152,061.1*** (17,929.6)
τ^{PSW}	0.03 (0.03)	-0.19** (0.09)	-0.28*** (0.06)	-0.10** (0.04)	-0.31*** (0.07)	-0.05 (0.06)	0.10*** (0.01)	-116.3 (88.00)	-5,821.3 (4,480)	-20,644.1*** (3,817)	-33,117.9*** (5,393)	-6,420.5 (4,537)	-147,536.9*** (22,569.1)
τ_{Adj}	0.02 (0.02)	-0.22*** (0.03)	-0.29*** (0.02)	-0.11*** (0.02)	-0.33*** (0.02)	-0.06*** (0.02)	0.12*** (0.01)	187.30*** (68.02)	81.7 (4,350.9)	-14,900.2*** (4,339.2)	-27,825.7*** (5,664.8)	-299.1 (4,360)	-114,595.3*** (11,931.5)
τ_{Adj}^{PSW} – 50yrs horizon for LUC	0.01 (0.03)	-0.02 (0.03)	-0.07** (0.03)	-0.05 (0.03)	-	-	-	-	-	-	-	-	-
ATE_{Adj}^{PSW}	0.05 (0.05)	0.01 (0.07)	-0.19*** (0.05)	-0.16*** (0.04)	-0.19*** (0.06)	-0.15*** (0.04)	0.12*** (0.01)	-31.23 (105.03)	-7,231.8 (7,770.8)	-22,965.7*** (6,719)	-35,789.3*** (7,942.)	-7,245.21 (7,734.40)	-131,831.4*** (9,375.6)

Note: * p<0.1; ** p<0.05; *** p<0.01 and (.) are standard errors. *dLUC GHGE corresponds to Gross GHGE and on-farm carbon sequestration, while dLUC + iLUC account for carbon fluxes related to indirect LUC. dLUC + iLUC + Seq. Practices 2.5% and 97.5% are the lower and upper bounds of the bootstrapped estimation of the displacement factor used in the computation of the GHGE from iLUC. Value added is Total revenue minus inputs costs while Gross Margin corresponds to Value added minus labor costs.*

Figure 3 Decomposition and ATT of carbon footprint and gross margin.



Whiskers indicate standard deviation in frames a, b, d and e and the 95% confidence interval of the ATT in frames c. and f. Direct land-use changes (dLUC) cover permanent grassland <-> cropland conversions within the farms, practices cover the changes in the share of temporary grassland in crop rotations, the cumulated length of hedges and the amount of nitrogen fertilization on pastures. Indirect land-use changes (iLUC) cover forest <-> cropland conversions overseas as a result of changes in concentrates use due to differences in nutritive capacity between grass and maize. All graphs use the weighted data from the propensity score procedure.

The most common indicator of environmental performance - gross GHGE without accounting for land use and management - is not significantly different between organic farms and their conventional counterparts (τ_{Adj}^{PSW}=0.01 kgCO2e.L^{-1} or +1%, p-value = 0.283, Figure 3c. & Table 2). This results from two opposite effects balancing one another: lower yield versus lower emissions per hectare. On the one hand, organic farms tend to be less productive in liters ha^{-1} or liters cow^{-1} (Gaudaré et al. 2021). Reinforcing this productivity effect, one should note that half of the GHGE of dairy farms stem from enteric fermentation, which is decreasing in cow productivity and in the share of concentrates in cow diet (Zehetmeier et al. 2012). As conventional farms are more productive, mostly because they use more concentrates, their cows emit less methane than their organic counterparts that are mostly fed with grass and hay. However, these higher methane emissions for organic farms are offset by lower emissions from feed and mineral fertilizers.

When the carbon sequestration or emission resulting from of land use changes within the farms (dLUC) are introduced, the GHGE of organic milk are also not significantly different from the conventional counterparts' ones (τ_{Adj}^{PSW}=-0.06 kgCO2e.L^{-1} or -6%, p-value = 0.33, Table 2). As expected, organic farms have a higher share of permanent grassland than their conventional counterparts do – 45% of agricultural land versus 36% – and each additional hectare of permanent grassland lowers farm emissions by 3.7 $tCO_2e.yr^{-1}$ (Figure 3 & SM.2) in our model, but this is not sufficient to produce a significant difference in carbon footprint. This higher share of permanent grassland is partly mandated by the technical specifications of organic milk production, which require a minimal 60% of grass or hay in the feed mix and at least 60% of this feed mix must be produced on-farm (European Commission 2008), and partly incentivized by the high prices of organic feed.

The ATT of organic farming on the dLUC + practices GHGE is negative and significant (τ_{Adj}^{PSW}=-0.185 kgCO2e.L^{-1} lower GHGE or -19%, p-value = 2e^{-06}, Table 2). Thus, accounting for the impact of key management practices on carbon sequestration is necessary when comparing organic and conventional farming systems, as omitting these practices would lead to an incorrect conclusion that carbon footprint is not significantly different between organic and conventional milk. The difference in GHGE between the two farming systems is largely driven by a higher share of temporary grassland in crop rotation in organic farms – an average 72% versus 49% for the conventional weighted counterparts – although total nitrogen fertilization of permanent grassland is lower on organic farms – 92 kgN ha^{-1} versus 184 kgN ha^{-1} – and the density of hedges is comparable – 80 m ha^{-1} versus 107 m ha^{-1}. There again, the higher share of temporary grassland is likely driven by the technical specifications.

Whether and how to include estimates of GHGE from indirect land-use change (iLUC) in LCAs is heavily debated. On the one hand, basic economic theory predicts that lowered yields somewhere generates higher production elsewhere. On the other hand, estimating this elasticity and to which extent higher production occurs at the extensive margin is challenging, notwithstanding the moral dilemma of attributing this effect between importing countries which could reign in consumption and exporting countries which could regulate production practices (e.g. stringent land-use regulations can force growth to take place at the intensive margin). Including iLUC in the ATT estimates can thus be considered as conservative, especially here where we implicitly assume that demand is fully inelastic. It reduces the difference in carbon footprint between organic and conventional milk to -11% (τ_{Adj}^{PSW}=-0.13kgCO2e.L^{-1}, p-value = 2e^{-04}, Table 2). Indeed, the feed yields are lower in organic farms, thus virtually requiring – in our iLUC estimates – an average 6.9 tons ha^{-1} of concentrates to bridge the yield gap with their conventional counterparts, 13% of which we assume are grown at the expense of South American forests (see SM.2 for further details). Our LUC GHGE results differ from other LCA analyses which only include LUC in South American (rainforest and savannah deforested) stemming from direct soybean cakes demand from the surveyed dairy farms, such as Flysjö et al. (2012), Guerci et al. (2013) or Hörtenhuber et al. (2010).

As expected, the uncertainty associated with this iLUC estimate is substantial: when GHGE are estimated using the lower and higher bounds of the bootstrapped confidence interval for the displacement factor (SM.2), the ATT of organic farming ranges from -0.12 to -0.20 kgCO2e.L^{-1} but are still significant at a 1% confidence level (Table 2).

4.2. *Although less productive, organic farms have a similar economic performance than conventional farms*

The economic performance of organic farms - measured as their gross operating margin per annual work unit - is not significantly different from their conventional counterparts (τ_{Adj}^{PSW}=2,240€.AWU^{-1} or +3%, p-value = 0.518, Figure 3f. and Table 2). However, decomposing the gross margin shows that both revenues and inputs costs per annual work unit in organic farms are significantly lower than for their conventional counterparts (Table 2 and Figure 3f.). Indeed, the revenue of organic farms is 22% (τ_{Adj}^{PSW}=-13,300€.AWU^{-1}, p-value = 2.73e^{-07}, Table 2) or 44% (τ_{Adj}^{PSW}=-22,934€.AWU^{-1}) smaller than their conventional counterparts with and without accounting for the organic price premium, respectively. These lower revenues are however offset by lower costs (Figure 3f.), mainly due to a cheaper feeding strategy which mostly relies on grass and on-farm feed (Gaudaré et al. 2021). Ultimately, organic farms do not purchase any mineral fertilizers and less off-farm feed, two important farming expenses of conventional farms (Stonehouse, Clark, et Ogini 2001; van Wagenberg et al. 2017)). Labor costs are not significantly different between the two production systems (Figure 3f.) and the ATTs for the gross margin and the value added per annual work unit (gross margin without accounting for labor costs) are very close (2,240€.AWU^{-1} and 2,071€.AWU^{-1} respectively, both non-significant, Table 2).

These results are somewhat sensitive to the denominator of the economic indicator. Although annual work unit is the most common one, economic performance can also be expressed per hectare or per unit of product. Here, the difference in gross margin is also not significant when expressed per hectare (τ_{Adj}^{PSW}=96.5€.Ha^{-1} or +7%, p-value = 0.08, Table 2), but the difference in gross margin per liter of milk produced is significantly higher for organic farms (τ_{Adj}^{PSW}=0.12€.L^{-1} or +53%, p-value = 2e^{-16}, Table 2). This highlights a key difference in marketing strategy: organic farms aim for high margins per liter and produce smaller quantities while conventional farms offset smaller margins per liter with higher volumes. The absence of difference in labor costs is also mitigated by the denominator: for an economic performance expressed in €.ha^{-1} or in € per unit of immobilized capital, it may turn out to make a significant difference.

One should note that we only observe farms' gross margins, as we do not have information on taxes or no subsidies. Including taxes should not change our results: taxes are proportional on hired labor and production volume and the amount of the taxes are the same in organic and conventional systems. However, in our study period (2013 – 2015), subsidies differed slightly between organic and conventional systems. More precisely, for a given surface and herd size, organic farms receive on average the same amount of direct (coupled and decoupled) subsidies from the Common Agricultural Policy but received an additional subsidy of 148€ per cow on average in 2013 for conversion to organic farming or its maintenance (Dedieu et al. 2017). Thus, our ATT estimates of economic performances are likely suffering a weak attenuation bias and we estimate a lower bound of the true ATTs.

4.3. Green Deal's target of 25% of organic land would reduce French dairy sector's GHGE by 9.01 to 9.64%.

As mentioned in the introduction, the EU's Green Deal aims, through the Farm to Fork strategy, at increasing agricultural land devoted to organic farming up to 25% by 2030. In 2015, France produced 0.56 billion of liters of organic milk on 0.12 million hectares and 24.05 billion liters of conventional milk on 3.83 million hectares (FranceAgriMer 2016; Agreste 2015). Converting 22.08% of the conventional milk would be necessary to reach the Green Deal target. Applying our sample estimates for the ATT of organic farming on milk production (Table 2), we find that the conversion would reduce milk production by 7.40%, corresponding to a 2.200 $MtCO_2e$ reduction in emissions from the dairy sector. In addition, 3.61 billion liters of formerly conventional milk would have become organic, resulting in a further 0.48-0.67 $MtCO_2e$ reduction in emissions (dLUC+iLUC+practices and dLUC+practices respectively). Overall, the Green Deal target can be expected to reduce emissions of the French dairy sector by 9.64%, 7.40% through reduced production and 2.25% through the lower carbon footprint of organic milk (Table 3).

Table 3. Simulation of GHGE under the Green Deal's target of 25% of organic land

		Conventional	Organic	Total
2015	Milk production (GL)	24.05	0.56	24.61
	Gross GHG emissions ($MtCO_2e$)[1]	29.06	0.69	29.75
Green Deal target	Change in milk production (GL)	-5.43	3.61	-1.82
	Change in dairy sector's emissions due to changes in milk production	-22.08%	14.68%	-7.40%
	Change in dairy sector's emissions due to changes in milk carbon footprint (Gross+dLUC+practices)	-	-2.25%	-2.25%
	Change in dairy sector's emissions due to changes in milk carbon footprint (Gross+dLUC+practices+iLUC)	-	-1.62%	-1.62%
	Total change in dairy sector's emissions (Gross+dLUC+practices)	-22.08%	12.43%	-9.64%
	Total change in dairy sector's emissions (Gross+dLUC+practices+iLUC)	-22.08%	13.06%	-9.01%

This simulation of the climate change impact of the EU's target of organic farming has obvious limits. First, it implicitly assumes that conventional dairy farms are converted in proportion to their propensity score. While this assumption is the most sensible at the margin, it may be overstretched for such a large shift: indeed, the ambition

[1] Estimated based on the average gross carbon footprint of milk in our database (see Table 2).

of the Green Deal is so important that the number of converted farms would likely largely exceed the number of conventional farms with a high propensity score. Second, it assumes that the increase in organic milk supply and the decrease in total milk supply would not have significant effects on organic and conventional milk prices. Estimations of demand elasticities for dairy products in France in 2010 show a weak own-price elasticity for conventional milk, -0.578 in 2010 and cross-price elasticities ranging from 0.04 to 0.19 with other animal products (Bonnet, Bouamra-Mechemache, et Corre 2018). Another study shows that the own-price elasticity for organic milk is even weaker, reaching -0.38 in 2005 (Monier et al. 2009). Further research on the demand and supply prices' determination could shed some lights on this issue, especially in a highly integrated market such as the dairy sector. However, as the demand for organic milk is steadily increasing in France (Lambotte, De Cara, et Bellassen 2020), one might expect that organic milk price should maintain itself even after a 15% increase of supply.

5. Conclusion

Comparisons of the environmental and economic performances of organic versus conventional farms must be undertaken carefully. Here we demonstrate that organic milk has a 11-20% lower carbon footprint than its conventional counterpart, depending on whether indirect land-use change is accounted for. In addition, we show that economic performance is similar between organic and conventional farms. Without addressing the three common pitfalls of LCAs, results would have been drastically different. Without the proper and objective selection of counterfactual farms allowed by the extraordinary large LCA dataset we mobilized, the estimated difference in carbon footprint between organic and conventional farms are overestimated as they do not account for organic farms' self-selection into the organic production technology. Without accounting for GHGE related to land use changes and management, we would have misleadingly concluded to a similar carbon footprint between organic and conventional milk.

The latter effect is however very sensitive to modeling assumptions: extending the transition period from 20 to 50 years removes the significant effects of organic farming on all GHGE estimates except our central one (including dLUC and farming practices but not iLUC). Similarly, taking the lower bound of the bootstrapped displacement factor for iLUC increases by 50% the difference of carbon footprints between organic and conventional farming. This uncertainty is one of the arguments against the inclusion of biogenic carbon in LCAs. While there is little ground for neglecting direct land use changes and management changes as long as the sensitivity to the transition period is properly presented, there are stronger, more theoretical arguments to be cautious when considering indirect land-use changes. Our iLUC estimates only considers the lower yield related to the difference in grassland share between farms. The potential iLUC related to the lower yield of organic forage and, therefore, of the lower productivity in liters per hectare of organic farms is not considered. Our implicit assumption is therefore that French demand for milk is fully elastic and will adjust perfectly to a reduced domestic supply. To the contrary, others studies assume that demand is fixed (e.g. Searchinger et al. (2018), Smith et al. (2019)).

Using the average treatment effects on the treated of organic farming, we assess the climate mitigation potential of the EU's target of 25% of organic agricultural land with the example of the dairy sector in France. Our simulation shows that such a large-scaled conversion to organic farming would reduce French milk supply by 7.40% and that 14.68% of formerly conventional milk would be substituted by organic milk. The combination of these two effects leads to a 9.01 to 9.64% decrease of the French dairy sector's GHGE. We also highlight that we propose a simplistic simulation of the consequences of the *Green Deal*'s target, ruling out organic and conventional milk prices effects as well as additional potential production displacement overseas.

Finally, despite the propensity score weighting procedure, our results may still be biased by a selection process, as we do not observe farmers' know-how and their relationships or proximity with other organic farmers, producers' associations and markets, two factors that influence the probability to convert to organic farming (Latruffe et Nauges 2014). This limit could be overcome with a panel data of farm LCAs, offering a quasi-experimental setting and allowing for the fully correction of the selection bias as GHGE and economic performances could be assessed before and after the conversion to organic farming for each farm. Unfortunately, to the best of our knowledge, this kind of dataset does not yet exist.

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Appendix

A.1. Data description

Table A.1. Descriptive statistics of the variables

Variables	Description	Mean	St. dev.	Min	Max
Gross margin per L	Gross margin per liter of FPCM milk, in €.	0.237	0.062	-0.354	0.627
Gross margin per LU	Gross margin per annual work units in €.	75,698	37,650	-104,191	216,520
Gross margin per Ha	Gross margin per hectare in €.	1,783	707.3	-2,780	5,142
Gross GHGE	Gross GHGE per liter of FPCM milk, in kg CO2e per liter of FPCM milk.	1.161	0.164	0.678	2.403
dLUC GHGE	Gross GHGE + dLUC GHGE per liter of FPCM milk, in kg CO2e per liter of FPCM milk.	1.127	0.257	-1.915	2.205
dLUC + Practices GHGE	Gross GHGE + dLUC GHGE + impacts of practices per liter of FPCM milk, in kg CO2e per liter of FPCM milk.	1.116	0.218	-1.102	2.059
iLUC + Practices GHGE	Gross GHGE + dLUC GHGE + iLUC GHGE + impacts of practices per liter of FPCM milk, in kg CO2e per liter of FPCM milk.	1.142	0.188	0.439	2.491
Herd size	Number of milking cows.	87.583	35.182	20.7	368.7
Surface	Acreage of the farm in hectare.	62.890	30.7	15	337
Milk Production	Volume of FPCM milk sold, in kL.	413.1	182.8	59.8	2016.3
Slope	Average slope, communal level, %.[b]	5.156	3.386	0.242	44.461
Rainfall	Annual precipitation, communal level, mm.[a]	973.805	165.692	547	1,609
Temperature	Annual temperature, communal level, °C.[a]	11.079	0.907	7	13
Soil depth	Soil depth in cm.[b]	128.813	32.511	26.509	433.364
Silt	Share of silt in the soil in cm.[b]	46.446	13.14	5.804	66.7
Clay	Share of clay in the soil in cm.[b]	22.087	4.486	3.072	44.5
Sand	Share of sand in the soil in cm.[b]	27.777	15.316	1.584	80.3
Region	Administrative region of France (1 if Britany, 0 otherwise).	0.57			
Calcareous soil	Calcaerous soil, dummy (yes/no).[b]	0.081	0.204	0.000	1.000
Water regime	Water regime:[b]	1.246	0.215	0	4
Ph	Ph of the soil.[b]	6.039	0.58	5.107	8.000
	5 : Very acid				
	5.5 : Acid				
	6.5 : Neutral				
	6.5 : Slightly alkaline				
	8 : Alkaline				
Breed	Main breed of cow in the farm (1 if Prim' Holstein, 0 otherwise).	0.76			
Farming System	Type of farming system (1 if specialized dairy system, 0 if diversified system)	0.14			

a. The data were made available by Météo France through the *Observatoire du Developpement Rural* (ODR, INRAE).
b. The data were provided by the UMR INFOSOL (INRAE).

A.2. Evaluation of the propensity score estimation and the weighting procedure

Figure A.2a. Covariate balance before and after the propensity score weighting

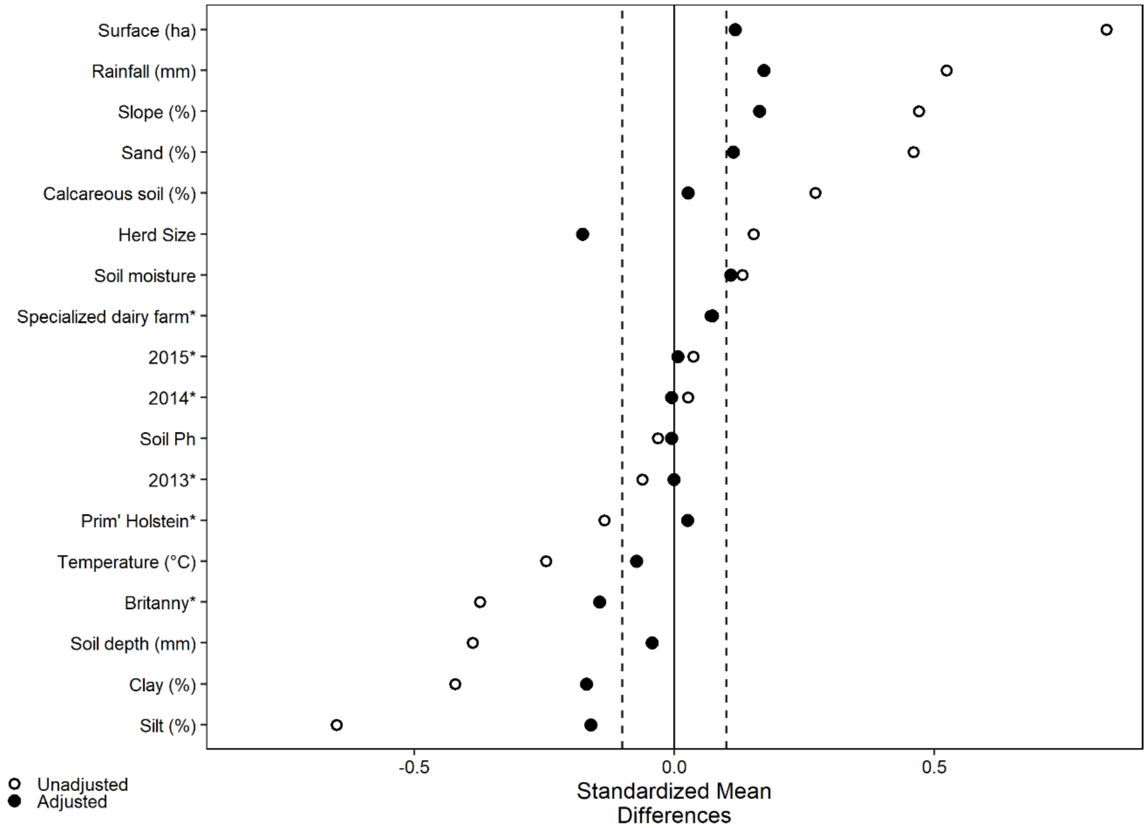
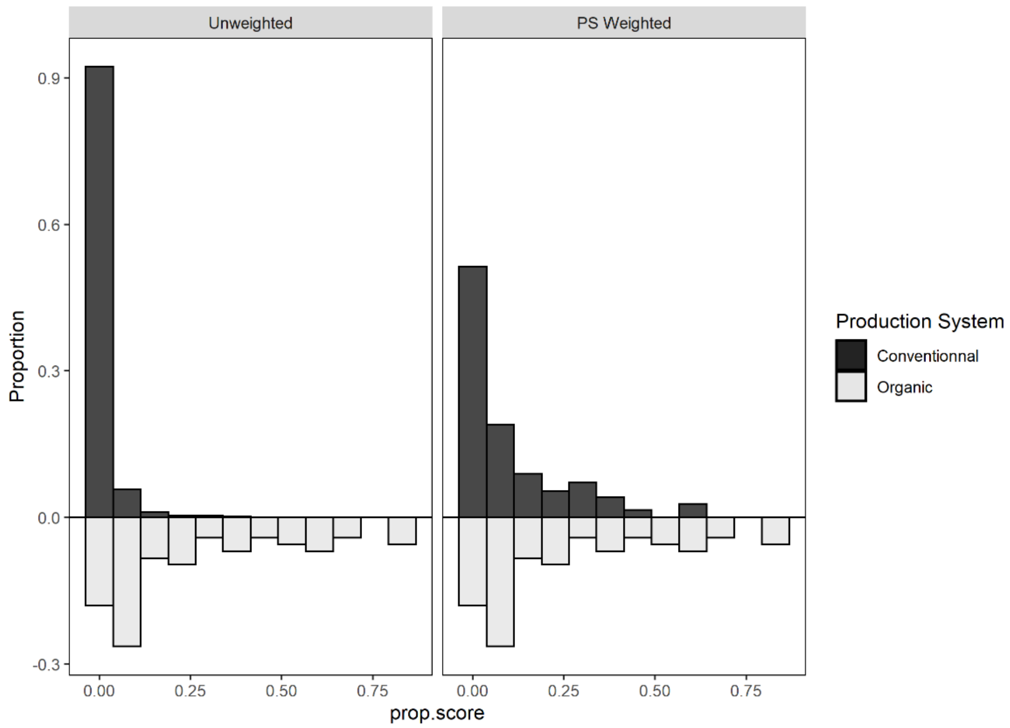


Figure A.2b. Distribution of the propensity scores among subsamples, before and after the propensity score weighting



A.3. ATT estimates with propensity score weighting and covariates adjustment with the exhaustive list of covariates

	Gross GHGE	dLUC GHGE	dLUC + Seq. Practices GHGE	dLUC + iLUC + Seq. Practices GHGE	dLUC + iLUC + Seq. Practices 2.5%	dLUC + iLUC + Seq. Practices 97.5%	Gross Margin per liter of milk	Gross Margin per hectare	Gross Margin per AWU	Gross Margin without price premium	Total Revenue	Value Added	Milk Production
	$kgCO2e.L^{-1}$	$kgCO2e.L^{-1}$	$kgCO2e.L^{-1}$	$kgCO2e.L^{-1}$	$kgCO2e.L^{-1}$	$kgCO2e.L^{-1}$	€.L^{-1}	€.Ha^{-1}	€.AWU^{-1}	€.AWU^{-1}	€.AWU^{-1}	€.AWU^{-1}	kL
τ_{Adj}^{PSW}	0.01	-0.06	-0.19***	-0.13***	-0.20***	-0.12***	0.12***	96.49*	2,240.07	-13,300.7***	-22,934.1***	2,070.87	-111,078.7***
	(0.03)	(0.06)	(0.04)	(0.04)	(0.05)	(0.04)	(0.01)	(55.28)	(3,462.99)	(2,954.91)	(4,090.56)	(3,462.55)	(11,226.4)
Surface (ha)	0.001**	-0.005***	-0.004***	0.001	-0.01***	0.002***	-0.0001	-11.84***	-221.46***	-205.51***	-322.25***	-226.71***	452.54
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.0002)	(1.18)	(61.21)	(52.13)	(65.83)	(60.71)	(803.93)
Silt (%)	-0.01***	0.001	0.001	-0.005	0.002	-0.01	0.002**	16.33***	830.60***	698.27***	865.59***	821.38***	49.52
	(0.003)	(0.01)	(0.004)	(0.003)	(0.005)	(0.004)	(0.001)	(4.46)	(265.49)	(223.77)	(324.57)	(264.16)	(36.09)
Rainfall (mm)	-0.0002**	0.0002	0.0001	-0.0002**	0.0001	-0.0003**	0.0000	-0.03	-9.43	-6.71	-9.39	-9.38	-428.73**
	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0000)	(0.18)	(10.86)	(9.11)	(13.12)	(10.85)	(194.84)
Herd Size	-0.001*	0.01***	0.004***	-0.001	0.01***	-0.002***	0.001***	11.70***	424.82***	374.73***	616.27***	428.48***	4,563.94***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0002)	(1.18)	(66.95)	(55.26)	(77.38)	(66.29)	(195.24)
Slope (%)	0.002	-0.02**	-0.01**	0.004	-0.01**	0.01*	-0.001*	-17.14***	-1,226.80***	-1,094.64***	-1,790.59***	-1,257.05***	-2,151.97**
	(0.003)	(0.01)	(0.01)	(0.003)	(0.01)	(0.004)	(0.001)	(4.85)	(289.26)	(250.76)	(358.76)	(286.55)	(1,047.33)
Prim' Holstein	0.05	0.16**	0.12**	0.04	0.14*	0.02	-0.02**	-124.62*	-8,451.66**	-7,022.00**	-6,820.30	-8,356.82*	-100.59
	(0.03)	(0.08)	(0.06)	(0.04)	(0.07)	(0.05)	(0.01)	(65.72)	(4,266.72)	(3,561.47)	(4,867.43)	(4,272.78)	(11,856.37)
Britanny	-0.06*	0.20***	0.07	-0.14***	0.11*	-0.19***	0.04**	137.35*	9,075.31*	9,599.01**	9,199.33	11,129.98**	8,503.45
	(0.03)	(0.07)	(0.05)	(0.04)	(0.06)	(0.05)	(0.02)	(73.13)	(5,268.89)	(4,451.59)	(6,153.59)	(5,222.10)	(14,344.19)
2014	0.003	0.07	0.08	0.03	0.09	0.01	0.02	27.07	-5,118.08	-4,248.42	-6,996.85	-5,150.33	24,289.35
	(0.04)	(0.07)	(0.06)	(0.04)	(0.07)	(0.05)	(0.03)	(99.76)	(4,992.65)	(4,227.43)	(5,710.85)	(4,960.71)	(19,314.39)
2015	0.09	-0.16	-0.12	0.08	-0.16	0.13*	-0.05**	-372.8***	-23,501.2***	-22,718.4***	-26,309.85*	-24,828.9***	10,896.60
	(0.06)	(0.11)	(0.09)	(0.06)	(0.11)	(0.08)	(0.03)	(87.07)	(8,527.71)	(6,533.47)	(14,925.27)	(8,490.47)	(26,726.40)
Sand (%)	-0.004**	0.01	0.004	-0.004*	0.01	-0.01**	0.0005	3.15	310.56	242.58	408.25	287.33	468.31
	(0.002)	(0.005)	(0.003)	(0.002)	(0.004)	(0.003)	(0.001)	(4.21)	(211.51)	(179.90)	(255.38)	(210.46)	(754.45)
Clay (%)	0.0000	0.02***	0.02**	-0.002	0.02***	-0.01	0.001	-5.70	-144.64	-118.22	-201.37	-173.14	-307.25
	(0.005)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.002)	(8.66)	(425.29)	(360.88)	(499.57)	(423.26)	(1,481.63)
Soil depth (mm)	-0.0003	0.001	0.001	-0.0001	0.001	-0.0003	-0.0002	-1.08	-137.80**	-121.82**	-153.99**	-139.64**	47.82
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0003)	(1.14)	(68.15)	(57.82)	(71.66)	(67.62)	(184.63)
Calcareous soil (%)	-0.09	-0.07	0.04	0.02	0.04	0.02	0.08	80.79	5,508.33	6,392.48	14,201.05	3,735.73	-33,645.45
	(0.10)	(0.21)	(0.15)	(0.10)	(0.19)	(0.14)	(0.05)	(201.75)	(11,530.86)	(9,629.92)	(15,390.33)	(11,473.64)	(34,830.51)
Temperature (°C)	-0.04**	0.15***	0.05**	-0.09***	0.08***	-0.13***	0.01*	73.50**	3,502.89*	3,273.85**	3,315.96	3,713.14**	9,947.71
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.01)	(33.92)	(1,814.97)	(1,515.32)	(2,057.20)	(1,812.48)	(7,786.96)
Specialized dairy farm	-0.05	0.001	-0.02	-0.06	-0.01	-0.07	-0.004	41.65	563.03	723.37	-1,306.47	456.31	27,503.57*
	(0.04)	(0.07)	(0.05)	(0.04)	(0.06)	(0.05)	(0.02)	(81.33)	(4,889.05)	(4,153.63)	(5,689.76)	(4,818.12)	(16,596.73)
Soil Ph	0.05	-0.14	-0.12	0.03	-0.15*	0.07	-0.02	-74.95	-3,482.73	-3,180.58	-3,692.35	-3,215.67	3,010.93
	(0.04)	(0.10)	(0.07)	(0.04)	(0.09)	(0.06)	(0.02)	(90.98)	(4,408.61)	(3,702.94)	(5,413.01)	(4,395.50)	(13,287.67)
Soil moisture	-0.04	-0.15	-0.10	-0.02	-0.12	0.001	0.03	-30.28	11,078.24	9,512.88	12,625.87	10,951.33	-47,445.18*
	(0.09)	(0.17)	(0.11)	(0.10)	(0.13)	(0.13)	(0.03)	(151.59)	(10,402.44)	(8,784.57)	(11,587.80)	(10,344.31)	(26,861.65)
Constant	1.98***	-0.77	0.43	2.56***	-0.001	3.12***	0.07	628.84	10,710.33	16,834.99	62,242.56*	30,021.62	-86,643.27
	(0.30)	(0.67)	(0.50)	(0.36)	(0.59)	(0.45)	(0.09)	(585.93)	(29,313.87)	(24,420.89)	(33,966.20)	(29,084.52)	(155,907.10)
Observations	3,054	3,054	3,054	3,054	3,054	3,054	3,054	3,054	3,054	3,054	3,054	3,054	

Note: Due to the presence of dummy variables, the treatment effects for organic farms cannot be directly compared to the constant. dLUC GHGE corresponds to Gross GHGE and on-farm carbon sequestration, while dLUC + iLUC account for carbon fluxes related to indirect LUC. dLUC + iLUC + Seq. Practices 2.5% and 97.5% are the lower and upper bounds of the bootstrapped estimation of the displacement factor used in the computation of the GHGE from iLUC. $^{*}p<0.05$, $^{**}p<0.05$, $^{***}p<0.01$ *and (.) are standard errors.*

A.4. ATT estimates of GHGE per hectare of organic farms vs their conventional counterparts

	Gross GHGE	dLUC GHGE	dLUC + Seq. Practices GHGE	dLUC + iLUC + Seq. Practices GHGE
	$kgCO_2e.ha^{-1}$	$kgCO_2e.ha^{-1}$	$kgCO_2e.ha^{-1}$	$kgCO_2e.ha^{-1}$
τ_{Adj}^{PSW}	-2,941.44*** (202.30)	-3,090.55*** (263.15)	-3,612.57*** (244.49)	-3,497.08*** (215.37)
Surface (ha)	12.06 (19.46)	27.73 (27.05)	26.14 (24.70)	14.00 (20.77)
Silt (%)	-0.27 (0.63)	0.12 (0.82)	-0.25 (0.81)	-0.55 (0.71)
Rainfall (mm)	6.52** (2.79)	7.12** (3.53)	6.67** (3.32)	6.20** (2.97)
Herd Size	-84.45*** (22.22)	-150.58*** (31.37)	-127.21*** (29.58)	-75.99*** (24.71)
Slope (%)	475.08 (290.64)	617.43 (376.93)	550.25 (359.07)	440.00 (315.87)
Prim' Holstein	434.95* (242.75)	1,435.48*** (318.12)	795.56*** (292.39)	20.61 (263.56)
Britanny	64.85 (332.71)	136.53 (406.21)	168.36 (394.94)	112.84 (355.39)
2014	392.34 (776.27)	-1,145.93 (923.13)	-729.86 (947.47)	461.60 (891.71)
2015	9.34 (14.71)	17.45 (22.16)	12.91 (20.04)	6.63 (15.85)
Sand (%)	18.88 (28.62)	39.28 (39.37)	20.01 (37.32)	4.20 (31.66)
Clay (%)	10.67*** (3.69)	11.12** (4.40)	11.20** (4.45)	10.85*** (4.04)
Soil depth (mm)	-2,092.38** (841.50)	-3,095.22*** (1,158.54)	-2,762.69** (1,097.99)	-1,985.94** (920.44)
Calcareous soil (%)	-151.40 (110.35)	283.15* (149.16)	21.75 (138.62)	-314.82*** (118.83)
Temperature (°C)	206.49 (249.01)	188.97 (345.54)	296.33 (323.86)	309.90 (280.02)
Specialized dairy farm	484.63 (324.49)	498.04 (467.02)	554.42 (433.83)	544.04 (352.46)
Soil Ph	-1,200.98** (556.59)	-1,916.81** (761.73)	-1,712.46** (715.88)	-1,158.02* (609.74)
Soil moisture	5,476.81*** (2,028.65)	-723.28 (2,818.20)	2,630.32 (2,662.39)	7,432.54*** (2,270.79)
Constant	-2,941.44*** (202.30)	-3,090.55*** (263.15)	-3,612.57*** (244.49)	-3,497.08*** (215.37)
Observations	3,054	3,054	3,054	3,054

Note: Due to the presence of dummy variables, the treatment effects for organic farms cannot be directly compared to the constant. dLUC GHGE corresponds to Gross GHGE and on-farm carbon *sequestration, while dLUC + iLUC account for carbon fluxes related to indirect LUC. dLUC + iLUC + Seq. Practices 2.5% and 97.5% are the lower and upper bounds of the bootstrapped estimation of the displacement factor used in the computation of the GHGE from iLUC.* $^{*}p<0.05$, $^{**}p<0.05$, $^{***}p<0.01$ *and (.) are standard errors.*