Conséquences économiques et environnementales d'un changement de production et de consommation vers des aliments sous signe de qualité

Mathieu Lambotte

THESE DE DOCTORAT DE L'ETABLISSEMENT UNIVERSITE BOURGOGNE FRANCHE-COMTE
PREPAREE A l'INSTITUT NATIONAL DE RECHERCHE POUR L'AGRICULTURE, L'ALIMENTATION ET L'ENVIRONNEMENT (INRAE)

Ecole doctorale n°593 : Droit, gestion, sciences économiques et politiques (DGEP)

Spécialité : Sciences Économiques

Présentée par

Mr Mathieu Lambotte

Thèse présentée et soutenue publiquement le 29 Octobre 2021 à Dijon

En vue de l'obtention du grade de Docteur de l'Université de Bourgogne Franche-Comté

Conséquences économiques et environnementales d'un changement de production et de consommation vers des aliments sous signe de qualité

Thèse dirigée par Valentin Bellassen et Stéphane De Cara

Composition du Jury :

Mme Zohra Bouamra-Mechemache	Directrice de recherche à INRAE, Toulouse, Rapporteur.
Mr Patrice Dumas	Chercheur HDR au CIRAD, Nogent-sur-Marne, Rapporteur.
Mme Adélaïde Fadhuile	Maître de Conférence des Universités, Grenoble, Examinateur.
Mr Olivier Allais	Directeur de recherche à INRAE, Saclay, Président du Jury.
Mr Stéphane De Cara	Directeur de recherche à INRAE, Saclay, Codirecteur de thèse.
Mr Valentin Bellassen	Directeur de recherche à INRAE, Dijon, Directeur de thèse.

Cette thèse a été financée par la Région Bourgogne Franche-Comté dans le cadre du projet de recherche AliDuTerr.

Remerciements

Je tiens tout d'abord à remercier mes directeurs de thèse Valentin Bellassen et Stéphane de Cara, pour l'encadrement de ces 3 années de thèse. Leur disponibilité et leur confiance m'ont aidé tout au long de ce travail de longue haleine. J'ai particulièrement bénéficié d'un suivi sans faille, de leur rigueur scientifique et de la liberté qu'ils m'ont laissée dans le développement des problématiques abordés et dans la manière d'y répondre. Je les remercie aussi d'avoir rendu possible ma venue en stage, le financement de cette thèse et l'obtention des bases de données qui ont rendu possible cette thèse. De même, je suis très reconnaissant pour l'accueil qui m'a été réservé, au CESAER tout comme à Economie Publique.

Dans la même lignée, je remercie le personnel administratif et d'appui à la recherche qui ont su m'aider durant ces presque 4 années au CESAER et les quelques jours passé à Economie Publique.

Bien évidemment, je tiens à exprimer ma gratitude aux membres du jury de cette thèse, Zohra Bouamra-Mechemache, Patrice Dumas, Oliver Allais et Adélaïde Fadhuile, avec une pensée spéciale pour les rapporteurs et le président du jury. Merci d'avoir pris le temps de lire mon travail et d'avoir partagé vos suggestions.

Je remercie aussi les membres de mon comité de suivi de Thèse, Stéphan Marette, Christine Boizoit-Szantai et Céline Bonnet. Je suis très reconnaissant pour le temps que vous avez passé à relire mes travaux au fur et à mesure de cette thèse et pour vos précieuses recommandations.

Mes remerciements vont aussi à ALISS et le projet Diet+, qui m'ont accordé l'accès à la base Kantar® et à leur serveur de calcul. Je remercie notamment Christine Boizoit-Szantai ainsi que Nicolas Gillet et son équipe pour l'assistance technique qu'ils m'ont gracieusement fournie tout au long de cette thèse.

De même, je remercie Catherine Brocas et Jean-Baptiste Dollé de l'IDELE, pour la confiance qu'ils m'ont témoignée en mettant à ma disposition les données d'ACV. Je suis notamment reconnaissant à Catherine pour les suggestions et l'aide technique qu'elle m'a apporté pendant 4 ans.

Evidemment, je remercie tous les collègues que j'ai pu croiser à Dijon ou Paris. Merci aux chercheurs et doctorants à qui j'ai pu présenter et discuter mes travaux en GTI, séminaires et apéros, vos recommandations ont toujours été utiles. Merci pour tous les moments de convivialité, qui in fine jouent énormément dans l'épanouissement d'un thésard. Une pensée spéciale va à Manu et Guillaume ainsi qu'au groupe de stagiaire extraordinaire d'il y a 3 ans.

Enfin, comme la vie extérieure au bureau est particulièrement importante pour l'équilibre mental du doctorant, je remercie Roman, Jean-Loup, Lore-Elène et Yacine qui ont fait en sorte que ces années soient toujours agréables, malgré les confinements et les hivers gris dijonnais.

Merci aussi à ma famille, qui même si je n'ai pas pu les voir autant que je l'aurais aimé (exil en Côte d'Or et Covid obligent) ont toujours su être là pour moi. Et évidemment, un incommensurable merci à Kyung-Pyo, notamment pour son soutien indispensable pendant ces 3 années.

Résumé de la thèse

Cette thèse analyse les conséquences d'une transition de la production et de la consommation vers des produits alimentaires de qualité. Nous évaluons les performances économiques et environnementales des exploitations agricoles labellisées (bio et AOP). Nous étudions aussi le comportement des consommateurs vis-à-vis des produits sous signe de qualité, en mettant l'accent sur la régularité des achats et leurs élasticités-prix.

Dans le premier chapitre, nous nous concentrons sur les exploitations laitières AOP et développons un modèle incluant l’impact des changements directs d’usage des sols et de plusieurs pratiques agricoles sur la séquestration de carbone dans l'estimation des émissions de GES (gaz à effets de serre). Bien que nous n'ayons pas pu trouver de synergies entre les performances économiques (marge brute) et environnementales (GES) des fermes AOP, nous avons identifié des leviers qui améliorent l'une des performances sans compromettre l'autre. Investir dans des équipements pour sécher le foin ou traire les vaches, limiter le chargement ou réduire la consommation de carburant augmentent la performance environnementale de 5 à 13 % sans nuire à la marge brute. L’intensification du travail ou la réduction de la part de protéines dans l'alimentation améliorent la performance économique de 7 à 21% sans augmenter les GES.

Dans le deuxième chapitre, nous poursuivons notre analyse des performances économiques et environnementales des systèmes d'élevage par une comparaison des exploitations laitières bios et conventionnelles en France. Nous développons notre modèle théorique de changement d’usage des terres pour intégrer l’impact des changements indirects sur les émissions de GES. De plus, nous mettons en place une pondération par score de propension pour contrôler les différences structurelles et pédoclimatiques entre les fermes biologiques et conventionnelles. Ainsi, nous constatons que le lait biologique a une empreinte carbone de 8,6 à 29 % inférieure à celle du lait conventionnel, selon si les changements indirects d’usage des terres sont pris en compte. Par ailleurs, nous n'avons pas trouvé de différence significative entre la marge brute des exploitations biologiques et conventionnelles.

Dans le troisième chapitre, nous analysons le comportement des consommateurs d'aliments sous signe de qualité. Nous montrons que ce comportement vis-à-vis des aliments bio est souvent *régulier* : pour un produit donné, les consommateurs ont tendance à toujours acheter la même version, soit bio soit conventionnelle mais rarement un mix des deux (*occasionnel*). Plus précisément, nous exposons que 29 % des ménages sont des réguliers d'au moins un produit bio mais que très peu de ménages sont des réguliers bio pour l'ensemble de leur panier. Cependant, ces consommateurs bios réguliers sont des acteurs clés puisqu'ils sont à l'origine de 28 % des achats du marché bio et jusqu'à 50 % dans le cas de certains fruits et légumes, des œufs ou du lait. À l'aide d'une modélisation à utilité aléatoire, nous

montrons que le comportement régulier envers les produits bio est plus important pour les produits davantage disponibles en magasin mais n'est pas influencé par le prix relatif du bio et du conventionnel.

Dans le dernier chapitre, nous estimons les élasticités de prix et dépenses des aliments bios et conventionnels en France de 2011 à 2018 en appliquant un système de demande censurée. Nous constatons que les élasticités-prix des produits bios sont considérablement plus élevées que celles des produits conventionnels et que les produits bios sont majoritairement des biens de luxe. De plus, les produits biologiques sont des compléments entre eux (élasticités-prix croisées négatives) et des substituts aux produits conventionnels (élasticités-prix croisées positives). La demande d'aliments bio est donc réactive aux changements de prix et une exemption de TVA pour l'alimentation bio augmenterait de 40% leur consommation.

Mots-Clés : bio ; signes de qualité ; exploitation laitière ; gaz à effets de serre ; comportement du consommateur.

Thesis' Abstract

This thesis analyses the consequences of a production and consumption shifts toward quality food. We have assessed the economic and environmental performances of quality-labelled farms, especially in comparison to their conventional alternatives. We have also analyzed consumers' behavior toward quality food, with a focus on the regularity of quality food purchases and price elasticities.

In the first chapter, we focus on PDO dairy farms and develop a model including the impact of direct land use changes and of several management practices on carbon sequestration in the estimation of farms' greenhouse gases emissions (GHGE). We uncovered several levers that improve one of the above-cited performance without compromising the other. Investing in equipment to more efficiently dry the hay or milk the cows, limiting livestock density, or reducing fuel use increase the environmental performance by 5 to 13% without impairing gross margin. Increasing labor use or reducing the amount of protein in the diet enhance the economic performance by 7 to 21% without deteriorating the environmental performance.

In the second chapter, we continue our analysis of the economic and environmental performances of quality-labelled farming systems with a comparison of organic and conventional dairy farms in France. We develop our model of theoretical land use change to integrate the estimation of indirect land use changes in addition to direct LUC and the impact of management practices on carbon sequestration. Moreover, we perform propensity score weighting to robustly control for the structural and pedo-climatic differences between organic and conventional farms. Doing so, we find that organic milk has a 8.6 – 29% lower carbon footprint than conventional milk, depending on whether indirect land use changes are accounted for. In addition, we could not find a significant difference between the gross margin per labor unit of organic and conventional farms.

In the third chapter we analyze purchase behavior of quality food consumers. We uncover that consumer attitude towards organic food is often *regular*: for a given product, consumers tend to either purchase it always organic or always conventional but not often a mix of both (*occasional*). More precisely, we uncover that 29% of the households are *regular* for at least one organic product although very few households are organic regulars for their entire basket. However, these regular organic consumers are key actors for marketing strategies or public policies as they are responsible for 28% of the purchases of the organic market and up to 50% for some fruits and vegetables, eggs or milk. Using a random utility modelling, we show that regular organic consumers are in general wealthier, urban, have a higher professional status, are more likely in couple and have relatively less children. Regular organic behavior is more prominent in products categories that are more widely available in all types of shops but does not seem influenced by the relative price of organic products compared to their conventional alternatives.

In the fourth and last chapter, we estimate price and expenditures elasticities of organic and conventional food in France from 2011 to 2018 using the same scanner data and applying a censored demand system. We uncover that own-price elasticities of organic products are considerably larger than conventional products and that organic products mostly are luxury goods (expenditures elasticities are more than unity). Moreover, organic products are complements among themselves (negative cross-price elasticities) and substitutes of conventional products (positive cross-price elasticities). Organic food demand is thus reactive to price changes and an exemption of VAT for organic products could increase their market share by 40%.

Keywords: organic; quality food; dairy farms; greenhouse gases; consumer behavior.

List of content

General Introduction

Motivation

Agriculture and environment nexus

Agriculture is a complex interaction of human, environmental and technological elements: labor and capital are mobilized to convert natural resources (water, soil, solar energy…) into food, fiber or fuel, in conjunction with a more or less intensive technology. As such, agriculture is a nature-based activity in a managed ecosystem: natural resources are used as inputs in the production process, and natural components are also produced as environmental externalities, in addition to food. The quantity of natural elements used and generated during agricultural activities varies greatly depending on the technology used and the activity. Intensive poultry farming, in batteries, uses very little land – at least directly – whereas maize production involves a large quantity of local water and land. Similarly, some agricultural activities create positive environmental externalities, such as landscape and species diversities in highly diversified farming systems, while all generate negative externalities, albeit in variable quantities, like greenhouse gases emissions (GHGE) in livestock farming or water and soil pollution with fertilizers and pesticides.

Agriculture and negative environmental externalities

The majority of modern agricultural systems and production techniques create negative environmental externalities. Indeed, since the 1950s agriculture activities have been intensifying worldwide due to the development of mechanization and chemical fertilization. With these innovations, agricultural systems have been deeply transformed to be able to feed a fast growing population. However, chemical fertilizers and pesticides have profoundly altered ecosystems and the environment. At the same time, dairy and meat products' consumption has increased worldwide, due to revenue increase and the associated diet changes in most regions.

Around 62% of European rivers are in poor chemical status, mainly because of fertilizers and pesticides' pollution by agricultural activities (European Environment Agency, 2018). 21% of the threatened or near-threatened species of the International Union for the Conservation of Nature (IUCN) Red List are in danger because of agricultural activities (Maxwell et al., 2016). Moreover, the agricultural sector is responsible for 25 – 30% of global GHGE (Steinfeld et al., 2006), the main driver of climate change. Climate specialists established that a 2°Celcius raise of global temperature would greatly endanger current and future humans' generations as well as other living species on Earth. To limit climate change to a 1.5°C average warming by 2100, GHGE should decline by 45% before 2030 and reach net zero around 2050 (Masson-Delmotte et al., 2018). To reach this goal the agricultural sector and especially the livestock sector, contributing to 80% of the agricultural GHGE (Gerber et al., 2013), should be mobilized.

Greening of conventional agriculture and its limits

For a long time, the international politic arena and to a lesser extent, the scientific one, have believed that technology, science and rationalization would allow environmental efficiency improvements of conventional agriculture large enough to achieve the GHGE' reductions planned for 2050. However, this technicist vision has been shown to be too optimistic, as only a 20% reduction of GHGE is believed to be achievable by technical means in the conventional agricultural sector, including mitigation possibilities through waste and food loss reductions, lower use of fossil energy or improved management of fertilization and manure (Röös et al., 2015; Tukker et al., 2011; Weidema et al., 2008). These limited possibilities are due to the fact that most of the GHGE are intrinsic to conventional agricultural production, as nitrous oxide emissions through on-field mineral fertilization or methane emissions from the ruminants' enteric fermentation (Edjabou and Smed, 2013; Wirsenius et al., 2011). In the case of France, no more than a 10 - 20% decrease in GHGE can be achieved without decreasing the number of cows and livestock production (Pellerin, S. et al., 2013). A straightforward conclusion is that in order to reach adequate GHGE reductions, not only conventional agriculture should be rethought, but also the wider food system, including consumption choices.

Quality-labelled farming as a mitigation policy

In parallel with the raising awareness of climate change consequences and the central role of modern agriculture in global GHGE, alternative agricultural production techniques, such as organic farming, have received a growing attention. Indeed, developing organic food and other quality labels (*Protected Designation of Origin, "Label Rouge",…*) has been advocated as a way to reduce the GHGE of the agricultural sector (Bellassen et al., 2021; European Commission, 2020). Organic farming uses less fertilizers and pesticides which reduces nitrogen emissions and water pollution and enhances soil fertility and biodiversity (Mäder et al., 2002). Moreover, organic and other quality-labelled livestock farming is more extensive and stores more carbon in the soil, which contribute to mitigate global GHGE (Reganold and Wachter, 2016). The organic farming regulations in dairy farming also limits the use of imported feed and concentrates and imposes that a majority of the cows' feed is produced on-farm and based on grass and hay (European Commission, 2008). Reinforcing the autonomy of dairy farms and reducing feed imports, notably soy bean cakes – which have a heavy carbon footprint because they are mainly produced in South American at the expense of crucial carbon sinks (savannah and tropical forest (Overmars et al., 2015)) – contributes to mitigate GHGE from the livestock sector. PDO dairy farming regulations (*cahiers des charges*) are also limiting the use of concentrate feed and imposing pasturing as soon as climatic conditions allow it.

An avenue worth exploring to reduce GHGE would thus be a shift in the quality of food produced and consumed, from a low quality food with heavy environmental externalities (conventional farming, especially animal products) to a higher quality (organic, designation of origins products) of food, with a lower share of animal products in the diet. From the farmers' side, quality-labelled production generally implies lower productivity due to the restrictions in the use of fertilizers, pesticides or feed concentrates for example. However, as quality-labelled products sell at a higher price, the farmers' profitability may be maintained or even increased. In parallel, certified food consumption has been strengthening in France, with an annual growth of the organic market of 15% (Agence bio, 2019), reaching 5% of the food market in 2018, while PDO, PGI and "Label Rouge" products represent 2.3%, 1.8% and 1.5% respectively (INAO, 2019). This durable increase in certified food consumption indicates that demand for such products has the potential to be strong enough to maintain high prices for farmers. Moreover, from the consumers' side, purchasing certified products is costly and a durable transition to certified food diets without increasing food expenditures would only be possible if the consumed quantity of animal products -especially beef meat - is reduced. This indirect effect, observed in the literature (Baudry et al., 2019; Boizot-Szantai et al., 2017; Lacour et al., 2018a), has a strong climate change mitigation potential, as reducing animal products is the main lever to reduce GHGE in the food sector.

Lower yields of quality-labelled farming and land use changes

However, as quality-labelled production suffers from overall lower yields (Seufert et al., 2012), developing such farming systems to a large scale would imply the intensification of agricultural activities elsewhere and/or the extension of agricultural land (Smith et al., 2019). This is problematic, especially as most existing comparisons of GHGE from quality-labelled and conventional farms, based on Life Cycle Analysis, do not integrate precise measures of the carbon released from such direct and indirect land use changes.

In addition, global food demand is expected to grow by 59-98% between 2005 and 2050, driven by demographic growth and steady income increase (Valin et al., 2014). During the same period, animal products' demand, driven by meat demand, could increase as much as 144%. These dynamics will also pressure land use changes and deforestation worldwide, independently of the development of quality-labelled farming.

Thus, promoting organic agriculture to a larger scale would only be possible if agricultural area increases, at the expense of existing forests and savannahs and/or if large structural changes affect food demand, especially a decrease in animal products' consumption. Indeed, reaching the GHGE reductions targets by 2050 would necessitate both less emitting agricultural production systems - such as organic and other quality-labelled farming - and shifts in consumers' diets, replacing animal products by vegetal sources of proteins. Fortunately, several studies show that consumers who purchase organic food also develop more sustainable diets and reduce their consumption of animal products, especially meat, which reduces the carbon footprint of their diets (Baudry et al., 2019; Boizot-Szantai et al., 2017; Lacour et al., 2018a). However, to the author's knowledge, a causal relationship between such a transition from carbon-intensive diets to less animal-based ones and the increase of certified food consumption has not yet been formally demonstrated. Although establishing such causal relationship is out of the scope of this thesis, we intend to provide new elements on consumer behavior toward certified products and the role such products may have in shifting toward less carbon-intensive diets.

Approach

Research Questions

This thesis clarifies the role quality food production and consumption may have in reducing GHGE and mitigating climate change. We analyze the environmental performance of French Protected Designation of Origin (PDO) and organic dairy farms to uncover if these production systems have lower GHGE than conventional systems. We improve the existing literature by including the GHGE from direct and indirect land use changes in the LCA of dairy farms. Moreover, we assess the economic performance of PDO and organic production systems, as such systems can be developed only if they offer an economic viable alternative to farmers. We also study extensive farms' characteristics and practices to uncover which ones could act as levers to increase environmental or economic performances. Studying the environmental and economic performances of certified agricultural production systems allows us to assert to which extent developing organic and PDO dairy farming may be sustainable and effective public actions in climate change mitigation?

However, encouraging the production of quality food would not have a strong impact if consumers are not appealed to such products. Indeed, farmers are not only sensible to public policies, such as schemes promoting PDO and organic production, but also to market prices and demand. Thus, this thesis also studies to which extent PDO and organic food may durably integrate consumers' diets. Particularly, we analyze two key elements of consumers' behavior toward quality food: the regularity of quality food consumption and the price elasticities of organic products. Indeed, we distinguish two types of quality food consumers, the *regular* and the *occasional* ones. *Regular* consumers of a quality food product purchase only organic or quality-labelled version of this product and are not strongly motivated by price incentives, but rather by environmental or health convictions. *Occasional* consumers purchase food products in both quality and conventional versions, and are more responsive to price changes. Thus, we examine to which extent regular consumption weights in quality food consumption and how prices, expenditures and products' availability influence organic food consumption. By doing so, we intend to uncover how public policies may sustainably increase certified food consumption, would a subvention of all certified food be effective? Or would policies targeted on products for which people are more likely to become regular consumers be more successful in achieving transitions to certified products-based diets?

Organization

As explained above, this thesis studies both the production and consumption of quality food products. As such, its organization follows two axes, one on the production of certified food and one on its consumption. In a first part, Chapter I and Chapter II focus on the environmental and economic performances of quality milk production in France. In a second part, Chapter III and IV analyze consumers' behavior towards organic food.

More precisely, Chapter I proposes an in-depth assessment of 95 PDO dairy farms in Franche-Comté and Savoy, estimating both their GHGE using Life Cycle Assessment and their gross margin. We assess whether quality food farming systems such as PDO dairy farming might be sustainable alternative to conventional farming. Specifically, we analyze several farming practices or farms' characteristics that are related to a better environmental and/or economic performances. We could not observe farming practices that create synergies between the economic and environmental performances but several practices are identified as levers that can improve either the economic or environmental performances of PDO farms without depressing the other performance. This chapter pays special attention to the functional units used in evaluating farms' performances and shows that harmonizing the carbon footprint or gross margin of farms by either their milk production or the agricultural area used yields sensibly different results, especially when the effects of direct land use changes (LUC) on soil carbon sequestration are included. The most intensive farms among the sample are considered to have undergone land use changes from pasture to cropland and so to have lost carbon sequestration potential compared to more extensive farms.

Chapter II broadens the scale of the previous analysis to 3,054 dairy farms in France, and focuses on organic and conventional farms, comparing the economic and environmental performances of both farming systems. We demonstrate the existence of a lower carbon footprint for organic milk and a similar profitability. This chapter develops a complex estimation of the effects of indirect land use changes on GHGE, accounting for the fact that organic farms are more extensive and produce less milk per cow or land use. Thus, the existence of extensive and organic farms implies that other farms need to intensify their production in a context of rapid world population growth, using soybean cakes in our mode. We allocate the soybean cakes production and the associated extension of agricultural area in South America to the organic farms' carbon footprint. The use of a large sample, in addition to the complete estimation of the farms' GHGE, including direct and indirect land use changes, allow us to a thorough comparison of organic and conventional dairy systems, using propensity score weighting to select proper counterfactuals for organic farms. We also show that organic and conventional farms, when properly compared, have similar gross GHGE but that including carbon sequestration and LUC in the GHGE' estimation concludes to a lower carbon footprint for organic milk.

Chapter III deepens the understanding of consumers' behavior toward quality food by questioning the existence of regular consumption behavior. Indeed, using large datasets of consumers' purchases (Kantar®'s scanner data), we develop a methodology to identify certified food *regulars*. We consider that *regulars* are consumers that once they purchase a product in a given quality (organic, conventional, *Label Rouge*…), always purchase this version of the product. We show that regularity plays a key role in organic consumption as 28% of the organic market is purchased by regular consumers, even if most organic consumers are regular for only a few key products (milk, egg, fruits and vegetables). Furthermore, we uncover the household characteristics and the products' attributes that influence such regular consumption behavior using logistic regressions and a random utility model. Products' availability and family (vegetables, eggs, milk etc.) play a key role in relation with regular organic behavior whereas prices or household characteristics do not strongly influence regular consumption.

Lastly, Chapter IV implements a censored demand system (Exact Affine Stone Index demand system) to estimate the price elasticities of food products in France, using again Kantar®'s scanner datasets. In continuity with our previous work, we focus on organic products and their own-price elasticities as well as their cross-price elasticities with both other organic and conventional products. As we show in Chapter III that regular consuming behavior is not the main factor explaining the dynamism of the organic market, we investigate the occasional behavior and more specifically the role of prices in influencing consumers' trade-offs between food of different quality, here conventional and organic qualities. We also incorporate information in the availability of organic products and on household socio-demographics in the estimation of these elasticities in the hope of deepening our understanding of consumers' behavior toward certified food. Using the estimated price elasticities, we simulate the impact a VAT exemption would have in rising organic food demand.

Chapter 1

Carbon footprint and economic performance of dairy farms: the case of Protected Designation of Origin farms in France

Note: This chapter is based on a paper published under the same title, coauthored with Stéphane De Cara, Catherine Brocas and Valentin Bellassen.

1.0. Abstract

This paper assesses the drivers of greenhouse gas emissions and economic performances for a sample of dairy farms Protected Designation of Origin dairy farms in France. Investigating caeteris paribus drivers of performance, we conclude that synergies are rare. Investing in farming equipment, optimizing fuel use or suppressing manure composting can however improve environmental performance by 5 to 13% without impairing profits. In parallel, increasing labor productivity and reducing the share of protein in the diet enhances the economic performance by 7 to 21% without increasing GHG emissions. On the debated merit of intensiveness, our analysis leans towards a negative influence of concentrates, especially protein-rich ones such as soybean cakes, both on economic and environmental performances. This result, consistent with previous studies on extensive systems, could be conditioned by a good know-how and management of grass.

Keywords: *Protected Designation of Origin; greenhouse gas emissions; gross margin; dairy farms.*

1.1. Introduction

With livestock supply chains accounting for 14.5% of global anthropogenic greenhouse gas (GHG) emissions (Gerber et al., 2013), the role of the animal sector is under increasing scrutiny in the climate change debate (M. Herrero et al., 2013). In France, meeting the ambitious GHG mitigation targets set by National Low Carbon Strategy – a reduction of its agricultural GHG emissions by 46% before 2050 (Ministère de la Transition Ecologique et Solidaire, 2018) – will require mitigation strategies in the livestock sector.

One major difficulty in reducing livestock-related emissions is that it may severely affect farm income (e.g. Pellerin et al, 2017). This is particularly true in the EU dairy sector, since the abolishment of milk quotas in 2015 has driven milk prices down which threatens the least productive farming systems (Salou et al., 2017b). Moreover, most farmers will only adopt greener farming practices if they do not threaten their profitability (Kiefer et al., 2014). While the classical economic response to this conundrum would be a tax on GHG emissions, the *gilet jaune* (Yellow Vests) uprising renders any new environmental tax very unlikely in the near future, which also pleads for addressing the environmental and economic performances simultaneously.

An interrogation that policy makers face and that we analyse is: can dairy farmers reduce GHG emissions while at the same time maintaining profits?

To approach this question in the case of extensive dairy farms, a rich and original dataset is mobilized (more than a thousand technical variables, used for life cycle inventories), with a relatively large sample size (n=95). Moreover, the farms observed in the dataset are all producing under a Protected Designation of Origin (PDO) label, with specific production constraints, in mountainous areas in eastern France. Thus, they share a homogeneously extensive "production situation", where the bio-physical and socio-economical drivers of the environmental and economic performances are common to all farms (Lechenet et al., 2016). In a specific production situation, as the external setting of the farms is homogenous, an analysis of the drivers of the performances will isolate the managerial and agricultural practices that explain the difference in performances among the farms, limiting endogeneity issues. Moreover, in French dairy systems, the variability in GHG emissions within each production system – intensive or extensive - is greater than the variations between production systems (Gac et al., 2014). Thus, there exists a knowledge gap in explaining the variability of the performances of farms sharing the same production conditions.

PDO farmers receive a "quality" premium (around 30%) on their milk selling price which enhances their profitability. To receive this premium, they must comply with specific requirements which limit both their production capacity and intensity, to enhance milk quality. These requirements are specifically related to extensive farming practices and could increase the environmental performance of PDO farming: low livestock density, lots of pastures, low use of concentrates, restricted use of fertilizers and so on (Hocquette and Gigli, 2005; Kop et al., 2006).

In this sense, the French government has pointed out the development of PDO farming as a way to achieve a low carbon agriculture while maintaining farmers' profitability (Ministère de la Transition Ecologique et Solidaire, 2018).

Despite large market share of the PDO quality sign in the dairy sector (e.g. 10% in the EU for cheese (Chever et al., 2012) compared with around 3% for the organic sign in France (Augere-Granier, 2018)), the economic and environmental performances of the PDO dairy sector have never been studied jointly. In the European dairy sector, this joint performance has only been investigated, to the authors' knowledge, in extensive Irish systems (O'Brien et al., 2015) and intensive Dutch systems (Thomassen et al., 2009). The question of the relationship between economic and environmental performances has also drawn a lot of interest with the assessment of the cost-effectiveness of mitigation measures, such as reducing stocking rates, nitrogen (N) fertilizers application or imported concentrates (Beukes et al., 2010; Doole, 2014). Moreover, whether extensive or intensive dairy systems pollute more is still debated and our study sheds some light on this issue, within PDO farms, which are mostly towards the "extensive" end of the spectrum (Dollé et al., 2013).

Thus, in this paper, we analyze the link between economic performance – gross profit per liter of milk produced and per hectare – and environmental performance – GHG emissions – including or not carbon sequestration, also per liter and per hectare. We go beyond existing literature by:

- Quantifying the impact of farms' characteristics or practices on the environmental & economic performances of PDO farms simultaneously.
- Using a large sample size within a homogeneous production situation (PDO farms in mountainous Eastern France) which allows us to focus on the role of management practices.
- Designing and implementing a novel and simple approach to account for carbon sequestration related to land-use and land management changes in a net GHG emissions indicator for environmental performance.

- Outlining a lead that may reconcile the contradictory results on the relative merit of extensive and intensive systems with regards to climate mitigation: we confirm that more extensive systems perform better with a higher share of grass, possibly because grass is more expertly managed in extensive systems (e.g. through proper drying) than at the intensive end of the spectrum.

1.2. Methodology and Data

1.2.1. Population characterization and notation

Our main data source is the field survey of 95 PDO farms in the Franche-Comté and Savoy regions, financed by the PDO consortia between 2013 and 2015 (Michaud, 2016; Perrard, 2016). These surveys gather all the necessary technical and managerial information that is used to compute GHG emissions via the CAP'2ER Life Cycle Analysis (LCA) tool. These surveys also provide detailed information on farmers' practices and farms' characteristics, such as the farm and herd sizes, the amount of concentrate feed used, the cereals produced and used on farm, the fertilizer use or the labor use. The average farm of our sample has 125 (σ (standard deviation) = 79) ha and 92 (σ = 51) cows, produces 348,158 (σ = 231,096) liters of milk per year, which amount to a productivity of 3,792 (σ = 758) liters per cow and 2,773 (σ = 1,205) liters per ha. The detailed descriptive statistics of our sample are provided in SM 2. In addition, PDO farms generally have Montbéliarde cows, fed mostly with grass and hay from set stocked pastures. The cows spend on average 208 days per year on pastures and otherwise are kept in barns with free stalls. The manure is usually not composted and stored in manure pit at least a week before being spread on the fields using a liquid manure tank. The farms are located in mountainous areas and do not use irrigation.

Consider a population of N_i farms (indexed by $i = 1 \ldots N$). 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…).

Denote by Π_i the gross profit, defined as $\Pi_i = p_i^O * O_i - p_i^X * X_i$ where p_i^O is a matrix of output prices and p_i^X a matrix of input prices.

Moreover, each farm emits an amount E_i of GHG as a negative externality of its production activity. As cropland and pastures can also sequester carbon in the soils, each farm sequesters an amount C_i of carbon. Thus, each farm has a gross GHG emission amount E_i and a net one, $E_i + C_i$.

To measure the economic performance, we consider two indicators, the gross profit per liter of milk (fat-and-protein corrected, with 40g/kg and 33g/kg respectively) produced (variable output), $\frac{\Pi_i}{M_i}$ and per hectare (fixed input), $\frac{\Pi_i}{A_i}$.

As indicators of the environmental performance we use the opposite of gross and net GHG emission per liter (fat-and-protein corrected) and per hectare, $-\frac{E_i}{M_i}$, $-\frac{E_i+C_i}{M_i}$, $-\frac{E_i}{A_i}$, $-\frac{E_i+C_i}{A_i}$ respectively. We use both a product-based and an area-based indicator to account for two diverging hypotheses on demand. Indeed, if demand is infinitely elastic or if there is no substitute for PDO products, consumers will fully adjust to any change in the quantity produced and the product-based indicators are irrelevant. To the contrary, if demand is inelastic or if standard products are perfect substitutes for PDO products, a reduced production in the PDO area will be offset by an increase in production elsewhere, diminishing the relevance of area-based indicators.

In sum, the variables of interest are $\Pi_i, E_i \ and \ E_i + C_i$ and the set of indicators

$$\bar{y}_i = \begin{cases} \frac{\Pi_i}{M_i}, \frac{\Pi_i}{A_i} \\ -\frac{E_i}{M_i}, -\frac{E_i}{A_i} \\ -\frac{E_i+C_i}{M_i}, -\frac{E_i+C_i}{A_i} \end{cases}.$$

1.2.2. Economic performance estimation

The gross margin Π_i is defined in this study as the difference between the farm's revenue and its costs, without accounting for taxes or subventions. The former includes the revenues from the sale of the farm's outputs O_i : PDO milk, animals, cereals and roughage. Factor costs include the buying costs of the farm's inputs I_i: forage, concentrates, fertilizer, electricity and fuel, contracted work and animals for the renewal of the herd. Family labor costs are valued at the average wage of paid labor (€20,965 per year).

To estimate the gross margin Π_i of each farm, these physical flows need to be multiplied by prices. The prices of most inputs and outputs are estimated using the FADN (Farm Accounting Data Network) average for the corresponding year and the corresponding NUTS2 region, with the following exceptions:

- Since the FADN does not identify whether a farm is PDO certified, the price of PDO milk for each year and each PDO area comes from the PDO unions (Agreste Bourgogne-France Comté, 2015; les fromages de Savoie, 2017).
- The prices of fertilizers and concentrates, which cannot be derived directly from the FADN, are obtained from Eurostat (2018).
- The buying and selling prices of dairy cows, cull cows and heifers is gathered from the *Ministère de l'Agriculture et de l'Alimentation*.

To test the robustness of this estimation, the average estimated profit is compared to the average reported profit for dairy farms in the Franche-Comté and Rhône-Alpes NUTS2 regions from FADN.

1.2.3. Estimation of the environmental performance

To assess the environmental performance, we focus on GHG emissions for two reasons: first because climate change is arguably one of the most pressing environmental challenge of the 21st century and second because GHG emissions are correlated with environmental impacts such as eutrophication, acidification and energy use (Guerci et al., 2013). Gross GHG emissions E_i - without carbon emissions/sequestrations related to land use and management - are computed using CAP'2ER, a GHG emissions calculator developed by the *Institut de l'Elevage* and following Life Cycle Assessment (LCA) guidelines (Institut de L'Elevage, 2013). The system boundaries are therefore "cradle-to-farm gate", including enteric fermentation, manure management, fertilizers, fuel and energy use, but also the GHG emissions due to the production of concentrate feed and fertilizers. Contrary to the default "energetic allocation" of CAP'2ER, these emissions are then allocated to the three products of farms – milk, meat and crops – in proportion of the share of each product type in the farm revenue (Baldini et al., 2017).

To estimate land-use related carbon sequestration (C_i), we also deviate from CAP'2ER for two main reasons. Firstly, CAP'2ER attributes carbon sequestration to static land management – such as permanent pasture – whereas the only stabilized results for cropland and grassland related carbon fluxes in the literature concern land-use changes (LUC). Indeed, the latest IPCC guidelines (IPCC, 2019) estimate carbon fluxes to be null for croplands and grasslands which did not undergo recent land use or management changes. Secondly because the sequestration factor used by CAP'2ER for permanent grassland derived from (Soussana et al., 2010) – 2.09 t CO_2eq ha^{-1} yr^{-1} – has been criticized as being too large to be consistent with the current knowledge about carbon fluxes and stocks in grassland (Smith, 2014).

In order to bridge this pitfall and provide a more robust estimate of land-related GHG emissions, we develop an innovative methodology based on land use and land management changes. The land use and land management of each farm in our sample is compared to a reference, average farm. We then estimate the carbon fluxes which 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 share of land uses (cropland vs permanent grassland) in our reference farm is set to the sample average (82% permanent pasture, 18% temporary pasture and cropland). Note that the choice of the reference farm does not impact our results on the differences in environmental performance within the sample. Carbon fluxes (sequestration or emission) associated to each type of land-use changes include both the actual flux resulting from the change and the alteration of future carbon fluxes implied by the change. For example, a farm which has 100% of pasture on 100 ha of total land is estimated to sequester 3.72 t CO_2eq. ha^{-1}.yr^{-1} on the 18 hectares which could have been converted to cropland to match the reference farm. The actual values and their sources are detailed in section 4.

Such an estimate is akin to direct LUC (*dLUC*) as defined by M. Herrero et al. (2013). Indirect LUC (*iLUC*) is a more controversial topic and its estimates are laden with high uncertainties. Nevertheless, we attempt to provide an upper estimate of it in the context of French PDO farms. In our case, *iLUC* could occur because one hectare of cropland (maize in our model) generally has higher yields than grassland in our sample and thus a larger nutritive capacity. Thus, assuming a constant demand, a farmer who converted some cropland into grassland would have to import feed to continue feeding the same herd. To produce this additional feed, either non-agricultural land is put into production (extensive margin) or the current production processes are intensified (intensive margin). We retain the extensive margin effect, and our study area being located in the Jura and Alps, non-agricultural land is most likely forest land. The combination of these two key hypothesizes – constant demand and extensive margin – yields an upper bound for the area estimate of iLUC. As such, they are not included in the indicator retained for "net environmental performance" and are only used as a robustness check (SM 10).

Using the formalization of Plevin et al. (2010), our reduced-form models of carbon sequestration for *dLUC* and *iLUC* are therefore expressed in equations 1 and 2.

$$dLUCseq_i = -LUC_i * \frac{dEmissionFactor}{Period} \quad (1)$$

$$iLUCseq_i = -LUC_i * DisplacementFactor_i * \frac{iEmissionFactor}{Period} \quad (2)$$

Where $DisplacementFactor_i = \frac{\frac{\mathrm{Nutri_G}}{\mathrm{Nutri_C}} * \mathrm{Yd_i^G} - \mathrm{Yd_i^C}}{\mathrm{Yd_{PDO}^C}}$ (see SM 1 for demonstration).

To compute the land-use related emissions (C_i), we use the parameters presented in Table 1.

Table 1. Specification of the carbon sequestration methods

Emission factor cropland to grassland (*dEmissionFactor*)	-74.3 t CO2eq.ha^{-1}	Source: (EFESE, 2019).
Emission factor forest to cropland (*iEmissionFactor*)	749.4 t CO2eq.ha^{-1}	Source: (EFESE, 2019).
Nutritious content (*Nutri*)	$Nutri_C$ = 3840 kcal.kg^{-1} $Nutri_G$ = 4010 kcal. kg^{-1}	feedtables.com, $Nutri_C$ being the value for maize.
Yield (*Yd*, t.ha^{-1})	Yd^C= 10.43 on average (min = 4.5, max =16), Yd^G= 5.5 on average (min = 0.3, max =7.9)	Source : surveys by Michaud (2016) et Perrard (2016), Yd^C being the value for maize.
Displacement Factor (*DisplacementFactor*)	0.55 on average (min = 0.10, max = 1.04)	Authors' calculation based on equation 3
Production Period (*Period*)	20 year	Default transition period in IPCC (2019).

In addition to the estimation of carbon sequestration from dLUC and iLUC, our method allows the estimation of the impacts of some management practices on biomass and soil carbon. Based on a recent review in France (Pellerin et al., 2019), we identify three practices that are relevant in PDO 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 LUC: a change in practice leads to carbon sequestration or emissions which saturate over time as soil and biomass carbon reach a new steady-state equilibrium. Similar to our LUC model, only the differences from the reference farm are therefore considered. Pellerin et al (2019) estimates that on average 63.7 linear meters of hedges sequesters 259 kg C.ha^{-1}.yr^{-1} in the soil and biomass on cropland and 242 kg C.ha^{-1}.yr^{-1} on pasture. Here, a linear meters of hedge is associated to 2 square meters of hedge and 1.5 square meters of uncultivated area both side of the hedge. As our dataset only contains the cumulative length of hedges for each farm, we allocate these hedges proportionally to grassland and cropland, based on the land-use of each farm. Emissions or sequestration are then added to the carbon budget of each farm based on the difference with the reference farm for both the amount of hedges in grassland and the amount of hedges in cropland. Nitrogen fertilisation on pasture stimulates the biomass growth and thus soil carbon sequestration. Several reviews conclude an almost linear relationship between nitrogen and carbon sequestration in grasslands, with an average ratio of 1.2 kg C per kg N (Eze et al., 2018; Fornara et al., 2012; Pellerin et al., 2019). Here again, differences in nitrogen fertilization – both mineral and organic – with the reference farm are translated into carbon emissions or sequestration, using the average ratio above.

The share of temporary pasture in rotation with crops also improves carbon sequestration in soil. For France, Pellerin et al. (2019) estimate that including 50% of temporary pasture in rotation with crops, compared to crops only, sequesters an additional 466 kgC.ha^{-1}.yr^{-1}. More generally, the relationship between the annual increase of SOC and the share of temporary pasture in the rotation follow a linear pattern from rotations dominated by crop (0% of grass) to rotation dominated by grassland (100% of grass) (Vertès and Mary, 2007). Accordingly, we assume that soil carbon sequestration and the share of temporary pasture in the rotation are positively and linearly correlated. To be consistent with our LUC estimates, temporary grassland is therefore assumed to increase carbon sequestration by 37.15 kgCO2e/% of temporary grassland/year. For example, as temporary grasslands represent 71% of the UAA (excluding permanent grassland) in the reference farm, a farm with no temporary grassland would be estimated to be emitting 2.6 tCO2e.yr^{-1}.ha^{-1} of UUA excluding permanent pasture.

The results based on this estimation of GHGE including impacts of management practices on carbon sequestration are however only used as robustness check because of multicollinearity issues (SM 9).

1.2.4. Econometric analysis on the whole sample

We aim at identifying the practices which create synergies between economic and environmental performances i.e. that influence in the same direction both performances. The annual variation of weather, production or prices, that can impact the environmental or economic performances, is accounted for by using year dummies and pedo-climatic variables (slope, temperature, rainfall, type of soil).

We use six separate Ordinary Least Squares (OLS) regression models (Model 1 to 6), with each of the indicators in the set $\bar{y}_i$ being the dependent variable of a model. As independent variables, we use farms' characteristics and practices, described in SM 2. The 6 separate regression equations follow the classical linear form:

$$Y = \beta X + \varepsilon \qquad (3)$$

where Y is a $[n * 1]$ matrix of one of the above 6 measures of performance for each farm, β is a $[k * 1]$ matrix of regression coefficients, different for each of the 6 models, X is a $[n * k]$ matrix, similar for each equation (SM 2) and ε is a $[n * 1]$ matrix of error terms, with n being the sample size and k the number of parameters.

The regression coefficients are compared to detect the explanatory variables that affect in the same direction both the environmental and economic performances (synergies). To identify practices which have an important effect on the performances, we calculate the effect size as the product of the difference between the first and third quartiles in X – to capture the actual variability in the sample – with the associated regression coefficients. Then, we divide these effect sizes by the average performance in the sample to obtain a relative effect size. For a given practice, this quantifies by how much the environmental or economic performance – per liter or hectare – could be increased if the median farm in the worst half of the sample would adopt the same practice as the median farm in the best half. All the statistical analysis is performed using R language (R Core Team, 2020) and the data visualization is done with the ggplot2 (Wickham, 2016) and corrplot (Wei and Simko, 2017) packages.

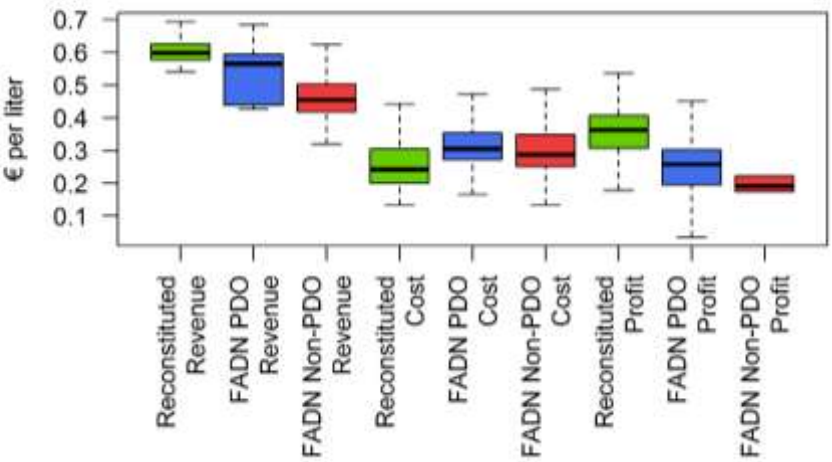
1.3. Results

1.3.1. Economic and environmental performances of PDO farms

Economic performance of PDO farms

The average estimated farm revenue in our sample is €210,813 and the average total factor cost amounts to €83,538. The average gross margin is thus €127,274. The averaged reconstituted revenue, cost and profit per liter are comparable to FADN averages for PDO farms in the same regions (Figure 1).

Figure 1. Comparison of the distribution of the estimated economic performance per liter and the FADN value (2013-2015)



The whisker boxes represent the average, first and third quartiles, and minimum and maximum.

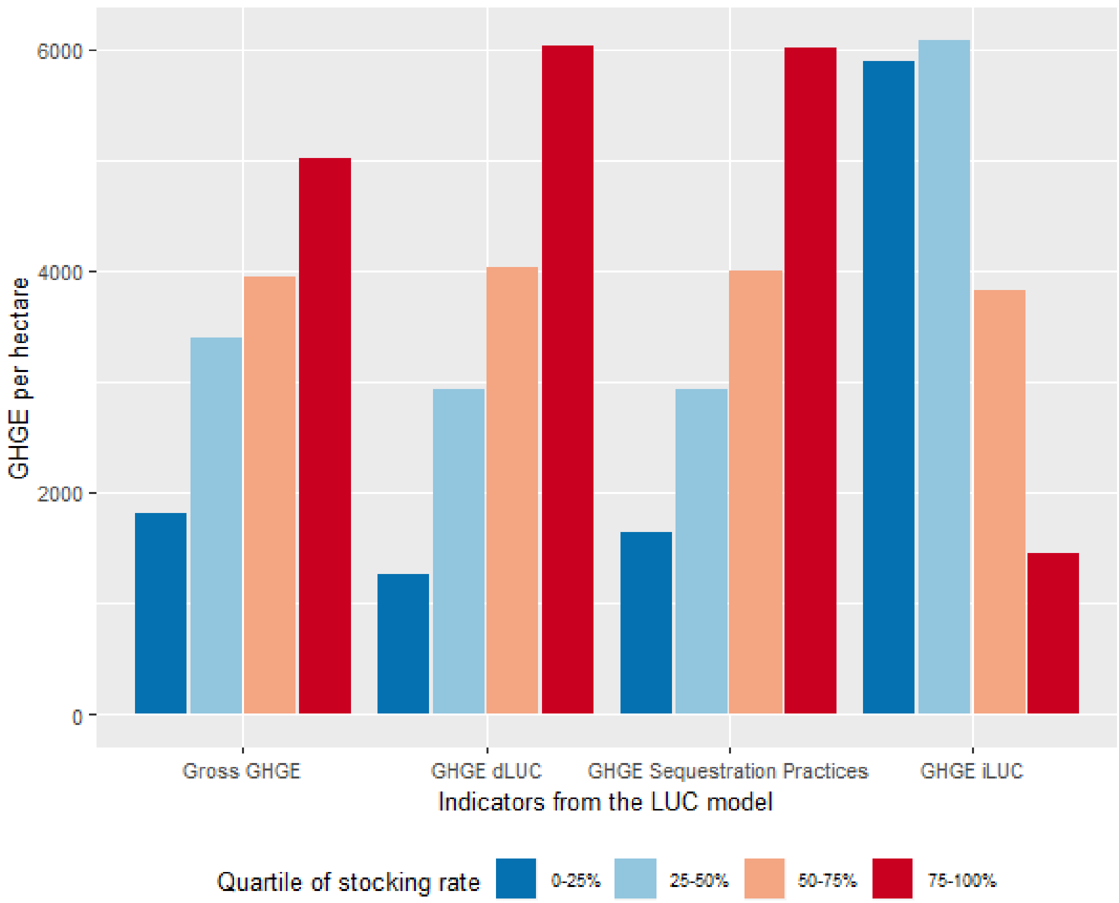
Gross profit per liter averages at €0.34 per liter and is higher than the FADN average for PDO, primarily because of lower costs. Indeed, concentrates costs may be underestimated in our estimation: it is one of the few cost categories for which we use prices from Eurostats (2018), as the FADN does not provide detailed prices for the concentrates purchased. These national prices underestimate this type of costs for PDO farms which are subject to specific constraints (many feed types are forbidden, local production of concentrates is mandatory …). Otherwise, the higher revenues and profits of PDO farms is confirmed.

Note that the standard deviation of our two economic indicators, profit per liter and per hectare, is large: 32% and 49% respectively (SM 2). This important variability is promising for the econometrical analysis.

Impacts of stocking rate and system boundaries on GHGE

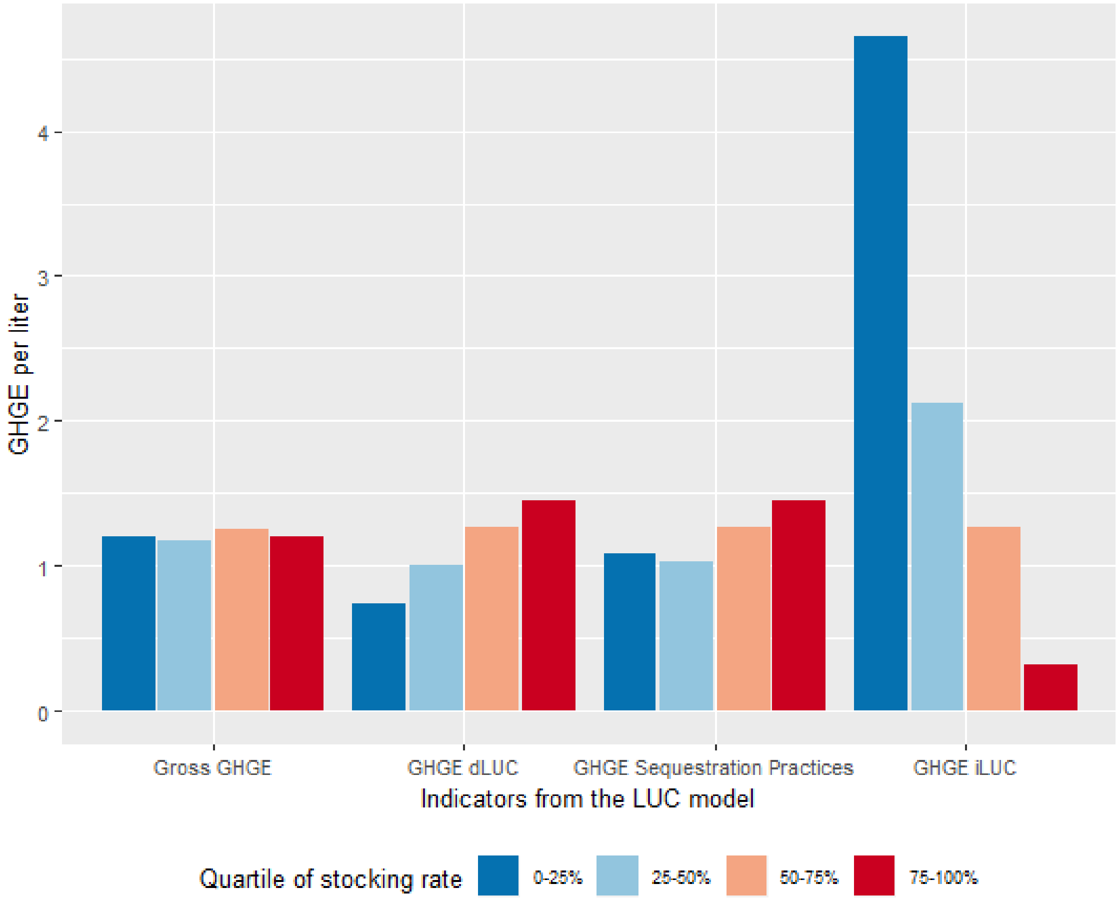
To illustrate the results of the theoretical LUC model, the GHGE are computed for each indicator, both harmonized per liter and hectare, and presented depending of the quartile of stocking rates, to represent the variation of farming intensity in the sample. When the GHGE are measured per hectare, the most extensive farms emit less, except when iLUC are accounted for. The difference of GHGE between the most extensive and intensive farms becomes larger with the increasing comprehensiveness of the LCA perimeter, until iLUC are included (Figure 2). Indeed, when iLUC are accounted for in the LCA, the GHGE of extensive farms is higher than intensive farms' ones, because the difference in nutritive capacity between maize and grass is high in PDO farms and thus the iLUC effects attributed to extensive farms are large.

Figure 2. Carbon footprint of indicators per hectare– with different LCA perimeters – per stocking rate quartile



The results are similar when the environmental performance is measured per liter, except that gross GHGE does not vary strongly with farming intensity (Figure 3).

Figure 3. Carbon footprint of indicators per liter– with different LCA perimeters – per stocking rate quartile

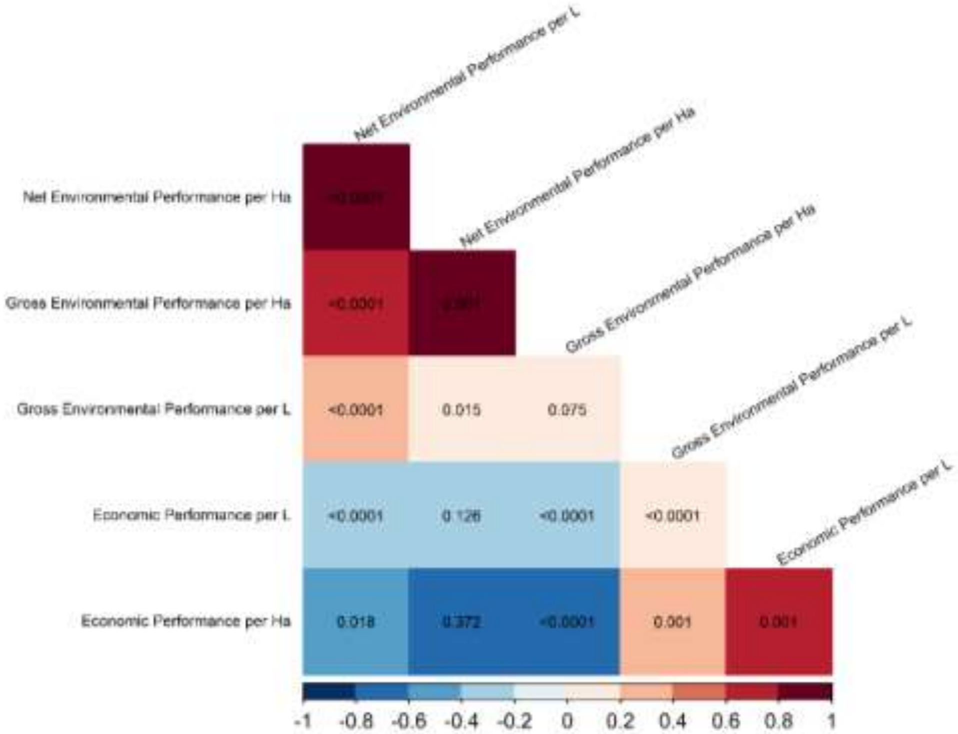


1.3.2. Relationships between the environmental and economic performances

Correlations between the environmental and economic performances

Analysing directly the correlation between the environmental and economic performances of the farms shows that environmental performance is mostly antagonistic to economic performance, with the exception of the gross environmental performance per liter (Figure 4).

Figure 4. Correlation of environmental and economic performances



The numbers in the cells indicates the p-values of the correlation tests.

No synergetic practice but many levers on either the economic or environmental performance.

No synergetic farming practice could be identified for the economic nor environmental performances: no variable with a significant regression coefficient for economic performance has a significant effect of the same sign on environmental performance and vice-versa (Figure 5,

Table 2). Trade-offs are also scarce: only the organic and mineral N spread on pastures improve environmental performance per hectare at the expense of economic performance per hectare. Several levers are however identified, which may improve either the environmental or economic performances by 7 to 21% without deteriorating the other.

Figure 5. Synergies, levers and antagonisms in economic and environmental performance

	Indicators per liter	Indicators per Ha
Synergy		
Lever on the environmental performance	Electricity per cow ↑ Organic N on pasture ↓ Manure composting ↓	Fuel per ha ↓ Share manure in organic fertilizers ↓
Lever on the economic performance	Labor use per cow ↓ Share protein in the diet ↓ Ecological Focus Area ↓	Labor use per cow ↓ Share protein in the diet ↓ Ecological Focus Area ↓
Trade-off		Mineral N on pasture Organic N on pasture ↓↑

A greenup arrow indicates an improvement of the indicator whereas a reddown arrow indicates a deterioration of the indicator. Only variables which have a significant and large impact on indicators are represented (p.value <5% and relative effect size > 5%). In the case of trade-offs, the first arrow always represent the impact on the environmental performances.

Table 2. Selected results of the OLS models

	Net Environmental performance per L (1)	Gross Environmental performance per L (2)	Economic performance per L (3)	Net Environmental performance per Ha (4)	Gross Environmental performance per Ha (5)	Economic performance per Ha (6)
Labor Use per cow	-5.00	-1.04	-6.08^{***}	1,745.81	6,819.09	$-15,319.7^{***}$
	(3.38)	(2.24)	(0.70)	(11,773.86)	(5,484.13)	(2,878.36)
Fuel per Ha	-0.002^{*}	-0.001	0.0002	-4.31	-5.22^{***}	0.61
	(0.001)	(0.001)	(0.0002)	(4.15)	(1.93)	(1.01)
Electricity per cow	0.0004^{**}	0.0003^{**}	-0.0000	-0.03	-0.54^{*}	0.17
	(0.0002)	(0.0001)	(0.0000)	(0.67)	(0.31)	(0.16)
Concentrate per cow	-0.0000	0.0000	-0.0000	-0.14	-0.42^{*}	0.02
	(0.0001)	(0.0001)	(0.0000)	(0.46)	(0.21)	(0.11)
Share protein in the diet	3.50	-1.91	-2.91^{***}	2,058.35	-5,106.24	$-8,415.21^{**}$
	(3.99)	(2.64)	(0.83)	(13,888.51)	(6,469.11)	(3,395.33)
Ecological Focus Area	-0.0001	-0.0002	-0.0001^{**}	0.69	-0.17	-0.43^{**}
	(0.0002)	(0.0001)	(0.0000)	(0.69)	(0.32)	(0.17)
Mineral N spread on pasture	0.003	-0.0002	0.0001	-14.56	-19.47^{***}	6.68^{***}
	(0.003)	(0.002)	(0.001)	(9.10)	(4.24)	(2.23)
Organic N on pasture	-0.004^{**}	0.0005	0.0000	-38.55^{***}	-32.19^{***}	7.57^{***}
	(0.002)	(0.001)	(0.0003)	(5.81)	(2.71)	(1.42)
Manure composting	-0.14^{**}	-0.09^{**}	-0.01	-306.13	-84.75	-97.04^{*}
	(0.07)	(0.04)	(0.01)	(235.60)	(109.74)	(57.60)
Share of manure in organic fertilisers	-0.69	-0.08	0.01	$-3,593.83^{**}$	-305.90	222.04
	(0.49)	(0.32)	(0.10)	(1,705.98)	(794.63)	(417.06)
Constant	1.01	-0.53	0.81^{***}	2,645.66	-43.49	$2,579.30^{**}$
	(1.23)	(0.81)	(0.25)	(4,267.82)	(1,987.90)	(1,043.36)
Observations	95	95	95	95	95	95
R^2	0.75	0.35	0.82	0.87	0.94	0.86
Adjusted R^2	0.65	0.09	0.75	0.81	0.91	0.80

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, standard deviations of the coefficients are included between brackets. Only variables which have a significant and large impact on indicators are represented (p.value <5% and relative effect size > 5%) The full table, including pedo-climatic variables and year dummies is provided in SM 4.

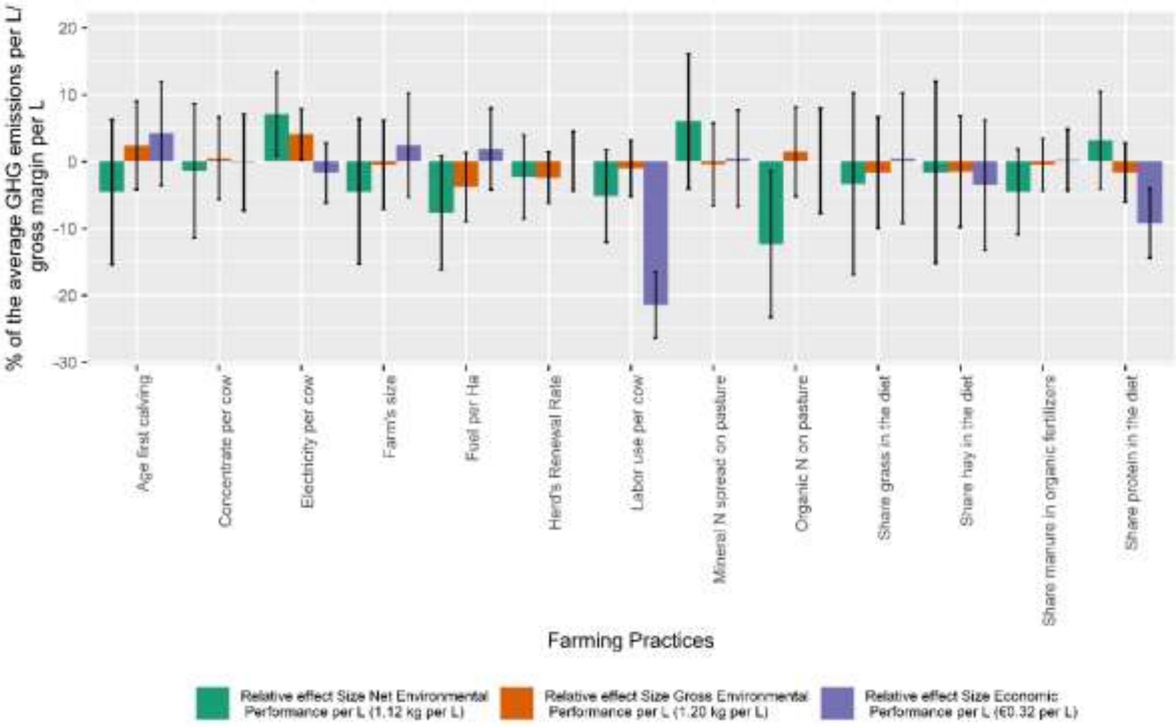
The independent variables retained in our models explain most of the variance of the indicators expressed on a per hectare basis, but a smaller share of per liter indicators (

Table 2, SM 4). This could be expected as more independent variables are expressed on a per hectare basis. Residuals vs fitted values plots do not indicate heteroscedasticity of the residuals or non-linear relationships between the variables, even if some outliers can be detected (SM 6). Shapiro-Wilk tests successfully assert the normality of the distribution of the residuals. To further assess the linearity of the relationships between the indicators of performances and the farms' inputs, a general additive model specification was tested but produced lower R^2 (coefficient of determination). With the exception of organic N spread on pastures, whose positive coefficients for models 1,2 and 6 saturate after 120 N unit per ha, no other input shows nonlinear effects (labor per cow, concentrates, N, P and K spread on cereals or pastures).

Several alternative indicators have been attempted to test the robustness of these results such as allocating all GHG emissions to milk production or restricting the perimeter of GHG emissions to the farms by ignoring emissions from the production and transportation of concentrates and fertilizers (SM 7 & SM 8). Indicators including the impacts of several management practices on carbon sequestration in the farms' GHGE have been estimated (SM9). Similarly, indicators including an upper bound estimate of indirect land-use changes are summarized in SM 10. Alternative specifications, with interaction effects (SM 11) or variable selection (SM 12) have also been tested.

Although these alternative specifications are sometimes useful in interpreting the results, none of them trigger major changes in the estimators or their significance. A notable exception is the inclusion of our higher-end estimate of iLUC which turns the amount of organic N on pasture into a significant positive lever on net environmental performance per liter. Another exception is the inclusion of the impacts of management practices on carbon sequestration, which turns the labor use per cow into a significant and

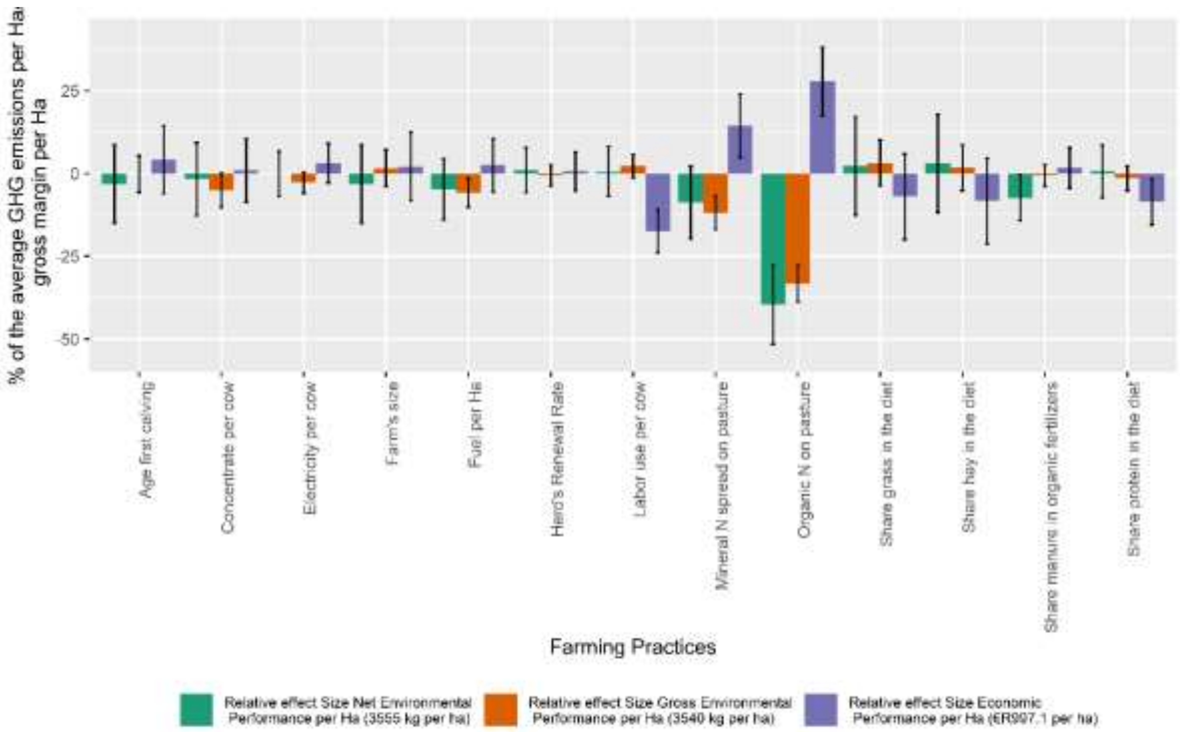
F



negative lever of the net environmental performance per liter and the age of first calving into a significant and negative lever of the net environmental performance per hectare.

The colored bars represent the relative effect sizes on the performance and the black lines the relative confidence intervals of the coefficients.

Figure 7. Relative effect sizes of selected practices on the net environmental and economic performances per hectare



The colored bars represent the relative effect sizes on the performance and the black lines the relative confidence intervals of the coefficients.

Impacts of levers on the environmental performance per liter

If the farmers of the quartile using the least electricity per cow could upgrade their hay drying equipment and reach the environmental performance of the upper quartile on electricity consumption, they would decrease their net GHG emissions by 0.08±0.07kg CO_2eq.L^{-1} (net environmental performance increased by 7.1% of total sample average) without any significant profitability change (Figure 6).

Similarly, farmers at the upper quartile of organic N on pasture would decrease their gross GHG emissions by 0.14±0.12 kg CO_2eq.L^{-1} (12.3% of total sample average) if they could move down to the lower quartile (Figure 6).

If farmers would stop the practice of manure composting, they would decrease their net GHG emissions by 0.14±0.13 kg CO_2eq.L^{-1} (13% of total sample average) (Figure 6).

Impacts of levers on the economic performance per liter

Reducing the labor use per cow, the share of protein in cows' diet and the ecological focus area could increase the economic performance of the highest half of the sample by €0.07±€0.02. L^{-1}, €0.03±€0.02. L^{-1} and €0.02±€0.02. L^{-1} respectively (21%, 9.2% and 7.2% of total sample average), all without any significant environmental damage (Figure 6).

Impacts of levers on the environmental performance per hectare

As expected, reducing fuel use per hectare could increase the gross environmental performance of the highest half of the sample by 208±153 kg CO_2eq.ha^{-1} (5.9% of total sample average) (Figure 7).
More interestingly, reducing the share of manure in organic fertilizers could increase the gross environmental performance of the highest half of the sample by 262±248 kg CO_2eq.ha^{-1} (7.4% of total sample average) (Figure 7).

Impacts of levers on the economic performance per hectare

Reducing labor use per cow, the share of protein in cows' diet and the Ecological Focus Area of the highest half of the sample could increase their economic performance by €174±€65.ha^{-1}, €86±€68.ha^{-1} and €120±€95.ha^{-1} respectively (17.5%, 8.6% and 12% of total sample average) (Figure 7).

Impacts of trade-offs on the performances per hectare

Reducing mineral and organic N spread on pastures in the highest half of the sample would increase their gross environmental performance by 419±182 kg CO_2eq.ha^{-1} and 1178±198 kg CO_2eq.ha^{-1} respectively (11.8% and 33.3% of total sample average) but decrease their economic performance by €143±€96.ha^{-1} and €277±104.ha^{-1} respectively (14.4% and 27.8% of total sample average) (Figure 7).

1.4. Discussion

1.4.1. Possible levers for performance improvement: tillage, logistics, milking equipment and labor efficiency

The econometric analysis shows that 6% can be gained on the environmental side by reducing fuel use without impairing economic performance. This possibility likely emerges from the potential to increase the share of grazed pasture (rather than mowed pasture): the share of grazing in the diet is negatively correlated with fuel use and when an interaction between the two is added in the regression model, its estimator is negative (although not significant, see SM 11). Another possible practice allowing the reduction of fuel use is the optimization of logistics, although this possibility may be constrained by the spatial distribution of fields and their distance from stables.

Conversely, a higher electricity use per cow increases the environmental performance per liter by 7% without decreasing the economic one. Indeed, electricity production results in little emissions in France (nuclear energy). Moreover, electricity use is mainly linked to milking equipment and the drying of hay, both of which increase milk production. Indeed, the share of hay is positively correlated to the electricity use and the estimate of the interaction is positive although not significant (SM 11).

Manure composting deteriorates the environmental performances per liter by 13%: most farm composters are not equipped to capture or flare methane, thus releasing considerable amounts of it during composting (Hao et al., 2004).

The share of protein in the diet largely reduces the economic performance, both per liter (21%) and per hectare (9%). Soy-based concentrates are indeed costlier and therefore do not seem to proportionally increase cow productivity. This practice is positively correlated with the amount of concentrates fed to the cows and thus decreases the environmental performance per ha, as the GHG emissions from the production and transportation costs of the concentrates are accounted for in our analysis.

Labor efficiency is also an avenue worth exploring to substantially improve economic performances per liter and per hectare without impairing environmental performance. Indeed, labor costs weight 53% of total costs, as PDO dairy farming is a labor-intensive technology (Bouamra-Mechemache and Chaaban, 2010). This lever seems partly related to economies of scale as our alternative models with variable selection mostly remove farm size from the set of dependent variables (SM 12). Natural constraints also play a role: labor intensity is correlated with steeper slope, scarcer rainfall and lower temperature.

Lastly, the positive influence of nitrogen on profit shows that PDO farms are not wasting nitrogen on pasture. However, the use of mineral and organic nitrogen on pasture is detrimental to environmental performance. Moreover, testing for an interaction between the amount of mineral and organic N spread on pasture reveals a negative and significant interaction effect on the environmental and economic performances. This indicates a potential synergy: where organic N fertilization is already high, reducing mineral fertilization would simultaneously increase both performances.

The share of grass in the diet, and in particular of grazing, is paramount in the technical specifications of these PDOs, but also in other quality signs such as organic farming. Here we do not identify these as important levers, neither for economic performance nor for environmental performance. This may be due to a rather small variance in these variables because all our farms follow the PDO specifications or to their correlation with fuel and electricity uses: the share of grass and hay in the diet are mostly excluded from the variables selection procedure, while the fuel and electricity uses are kept (SM 11).

1.4.2. Correlation between environmental and economic performances

The negative correlation between the environmental and economic performances per hectare is partly due to the intensification of farming practices: when production is intensified per unit of land, more feed, enteric fermentation and manure are taking place in the same area.

When the performances are measured per liter, we find a weak positive correlation between gross environmental and economic performances ($\rho = 0.18$) but a strong and negative correlation between the net environmental and economic performances ($\rho = -0.33$). O'Brien et al. (2015), who only use per liter indicators, find a positive correlation between economic and gross/net environmental performances ($\rho = 0.3$ to 0.5). This may be explained by the difference in carbon sequestration estimation method. Indeed, O'Brien et al. (2015) use a sequestration factor of 1.36 t of CO_2eq per ha of grassland and per year based on (Soussana et al., 2010), which overestimates carbon sequestration as discussed in section 1.2.3.

Thomassen et al. (2009) however find a negative correlation between the gross environmental and economic performances per liter ($\rho = -0.31$), in the case of intensive farms.

In Italy, Fiore et al., (2018) choose to cluster farms by their environmental performance (GHG emissions) and finds 3 clusters, with an antagonism between environmental and economic performances in each cluster.

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

In the case of extensive Irish farms (O'Brien et al. (2015)), the length of the grazing season is the most important lever on both the environmental and economic performances, i.e. creates a synergy. The conclusions drawn are that extensive livestock farming, limiting concentrate feed (which has a negative influence on both performances in their study) and better valorizing pastures and meadows can outperform more intensive systems (Ledgard et al., 2020), mainly because pastures imply carbon sequestration in soils. We verify these results, even when carbon sequestration is not accounted for (gross vs net GHG emissions), or integrates indirect land use changes (SM 9). Moreover, because both the length of the grazing season and the yield of milk per hectare or per cow are negatively correlated with GHG emissions per liter, O'Brien et al. (2015) show that extensive diets can also result in low carbon footprints. At the same time, by reducing feed costs, extensive grazing can reduce the farms' costs and thus extend their margins.

In the case of intensive Dutch farms, Thomassen et al. (2009) show that a high share of concentrate feed in cows' diet results in lower GHG emissions per liter thanks to higher milk productivity and lower emissions per unit of feed (Liang and Cabrera, 2015; Lovett et al., 2006). However, gross margin per liter is also reduced because of feed costs. Hence its conclusion is that environmental performance cannot be enhanced without decreasing farms' profitability.

Our results lie somewhat in between: similarly to O'Brien (2015), we find that concentrates may be overused in the sense that their reduction improves the economic performance in our sample of extensive farms. However, the environmental benefit is not sufficient to suggest a synergy when economic and environmental performances are expressed per liter.

We think that farmers' know-how in the grass management may provide the key to reconcile these contradictory results. Indeed, mowed grass tends to lose rapidly its nutritious content. The antagonism identified in Thomassen et al. (2009) may be explained by the limited presence of grazing in their sample farms, associated with a limited farmer know-how on grass management. In this context, a higher use of concentrates can be an effective way to reduce GHG emissions by lowering enteric fermentation (Lovett et al., 2008) and to increase profitability by rising the cows' productivity (Thomassen et al., 2009). But, as our study and the Irish case demonstrate, farms with high shares of pastures tend to create a synergy between environmental and economic performances as increasing the grass in the cows' diet can improve the digestibility of the forage and thus reduce the enteric fermentation and the CH_4 emission (Dillon et al., 2002), especially if the cut grass is harvested in an early maturity stage (Van Middelaar et al., 2014). The positive influence of hay drying equipment and positive – although not significant – effect of the square of the share of grass on the gross environmental performance per liter are consistent with this interpretation (SM 10): the grass management know-hows of extensive farmers allow them to increase their environmental performance with a higher share of grassland while intensive farmers would suffer from a degraded digestibility of grass when their share of grassland increases. Ultimately however, all these results rely on parameters choices for the digestibility of feed which are known to be very uncertain (IPCC, 2019).

Kiefer, Menzel and Bahrs (2014) compare organic and conventional dairy farms in Germany and also find that limiting concentrates use reduces GHG emissions and increases profitability. Similarly, Thomassen et al. (2008) recommend to decrease concentrate use per kilogram of milk, especially concentrates with a high environmental impacts (soy bean cakes). Moreover, Arsenault, Tyedmers and Fredeen (2009) find that the high concentrates use, fuel use and N fertilizers are the main drivers of environmental impacts in Canadian dairy farms. In their study, electricity is also an important contributor to GHG emissions, but our diverging results are straightforwardly explained by the sources of electricity: mainly nuclear energy in our French, context versus 75% of coal in Nova Scotia (Canada). Producing electricity with nuclear energy does not emit GHG whereas coal does, even if nuclear energy creates wastes that impact the environment but not through global warming.

In this debate, the originality of our study is to propose another statistical approach to this question and another method for the carbon sequestration, as well as using both product-based and area-based indicators. We find that the amount of concentrate only has a significant negative influence on the gross environmental performance per hectare. It also decreases net environmental performance per liter, but not significantly. As explained above, product-based indicators strongly respond to practices influencing cows' productivity. Thus, the non-significant effect of the concentrate use on the environmental performance may be explained by its limited effect on cows' productivity in our sample. Indeed, in our PDO sample, the capacity of the farmers to buy fodder crops and feed from the outside the PDO area is limited by the label's constraints, which forces them to develop other feeding practices, such as grazing and mowing.

1.4.4. Methodological advantages of the study

We find that using two indicators for performances, per liter and per hectare, is helpful in providing meaningful interpretations. Indeed, reasoning with product-based indicators presents the risk of underestimating the environmental impact of intensive practices (Salou et al., 2017a). As the per liter measure of the environmental performance is defined as the ratio between GHG emissions and milk production, if a practice increases the cows' productivity more than the GHG emissions, it will rise the environmental performance per liter. However, such practices would increase the absolute farm's GHG emissions, as well as GHG emissions per cow or per hectare. For example, in our study, only half of the significant practices impact both performances per liter and hectare (fuel per ha, share of protein in the diet and labor use per cow). The other identified levers are less robust and the recommendations to the farmers thus depend on the choice of the indicator. Note that the indicator selected for economic performance are correlated with other possible choices such as gross margin per labor unit.

Moreover, proposing several indicator of the environmental performances (gross GHGE, net GHGE and iLUC GHGE) increases the validity of the results, as including carbon sequestration and how management practices impact it as well as indirect land-use changes can by itself give the advantage to either intensive or extensive dairy farming as the most environmentally performant system (Meier et al., 2015).

1.4.5. Omitted variables bias

The main methodological limit in this study is related to the econometric models. Some important variables are likely to have been omitted, at least in the models with low adjusted r-square. Classical omitted variables, such as farmer's dynamism or competence, could be correlated with both the dependent variables and the practices, biasing the estimators (endogeneity). However, such omitted variable bias is limited: the heterogeneity of these classical omitted variables is likely to be limited in our sample (same production situation, same region, all PDO farms included in the same kind of farmers' association …). However, we cannot fully rule endoigeneity out and the causality of the relationships we identify must be carefully pondered. Other methods, such as farm system modelling or Data Envelopment Analysis can also successfully identify mitigation practices that increase the economic or environmental performances of dairy farms and that are similar to the levers discussed above (Beukes et al., 2010; Doole, 2014; Iribarren et al., 2011).

On a different note, our model of LUC and carbon sequestration does not account directly for farms' heterogeneity in pedo-climatic conditions (slope, temperature, sunlight, altitude, …) which affect soil carbon sequestration. However, we include these pedo-climatic conditions in the final-stage regressions to control for this heterogeneity.

1.5. Conclusion

Our regression models question the possibility of synergies between drivers of economic and environmental performance, but also the existence of necessary trade-offs. We identify however several levers: investing in milking equipment and hay drying equipment, reducing the livestock density, abandoning manure composting or optimizing fuel use increase the environmental performance by 5 to 13% without impairing gross margins, while increasing labor productivity and reducing the share of protein in the diet enhance the economic performance by 7 to 21% without increasing GHG emissions.

Our results also bring new insights on the debated merits of extensive milk farming, suggesting that concentrate use is detrimental to both economic and environmental performance as long as grass retains its nutritious content, for example via grazing. This would be worth confirming with a similar analysis on a sample containing both extensive and intensive dairy farms.

We also develop a novel and simple methodology for the estimation of land-use related emissions and sequestration based on potential land-use changes compared with a reference farm. By doing so, we provide new information on the sustainability of specific practices and a complete methodology that could be used in further studies on environmental and economic performances.

Beyond the methodological limit posed by a possible, although likely moderate, omitted variable bias, the main limit of this paper comes from the restricted study region and the possible sample selection. Indeed, we study the performances of the PDO farms among the same region and using only PDO farms in our statistical sample. While this can be beneficial to limit endogeneity, as we can compare farms that share a similar production situation, it limits the validity of any comparison with conventional dairy farming or PDO farming in other areas. Thus, the research on PDO farming and sustainable practices in agriculture could be improved by an analysis that would compare PDO farming in different countries or production situations. Reproducing our analysis for the conventional dairy sector in France and comparing the results could help determine if PDO dairy farming is more economically and environmentally performant, so more sustainable, than the conventional one. Furthermore, the levers of the performances that we uncover in this paper could be compared to the ones in the conventional dairy sector.

1.6. Supplementary Materials

SM 1. Details of Displacement Factor derivation

Nutritive capacity balance under a LUC:

$$LUC_i * (1000 * Nutri_C) * Yd_i^C = LUC_i * (1000 * Nutri_G) * Yd_i^G + \alpha * (1000 * Nutri_C) * Yd_{PDO}^C$$

where Yd_{PDO}^C is the average yield of maize in the PDO area, Yd_i^G is the average yield of grassland in the i^{th} farm, $Nutri_C$ is the gross energy (kcal/kg) for maize and $Nutri_G$ for grass.

We can derive that $\mathrm{Yd_i^C} = \frac{\mathrm{Nutri_G}}{\mathrm{Nutri_C}} * \mathrm{Yd_i^G} + \frac{\alpha}{LUC_i} * \mathrm{Yd_{PDO}^C}$

Thus, $\frac{\alpha}{LUC_i} * \mathrm{Yd_{PDO}^C} = \mathrm{Yd_i^C} - \frac{\mathrm{Nutri_G}}{\mathrm{Nutri_C}} * \mathrm{Yd_i^G}$

And $ConversionFactor_i = \frac{\alpha}{LUC_i} = \frac{\mathrm{Yd_i^C} - \frac{\mathrm{Nutri_G}}{\mathrm{Nutri_C}} * \mathrm{Yd_i^G}}{\mathrm{Yd_{PDO}^C}}$

SM 2. Descriptive Statistics of the farms' characteristics and practices.

Variables	Description	Mean	St. Dev.	Min	Max
Net Environmental Performance per L	Net environmental performance per liter, in kg CO2eq (opposite of net GHG emissions per liter).[a, c]	-1.12	0.43	-2.16	-0.26
Gross Environmental Performance per L	Gross environmental performance per liter, in kg CO2eq (opposite of gross GHG emissions per liter).[a, c]	-1.20	0.18	-1.65	-0.75
Economic Performance per L	Economic performance per liter, in € (gross profit per liter).[b]	0.32	0.11	-0.10	0.49
Net Environmental Performance per Ha	Net environmental performance per hectare, in kg CO2eq (Opposite of net GHG emissions per ha). [a, c]	-3,554.76	2,060.45	-5,149.29	-222.33
Gross Environmental Performance per Ha	Gross environmental performance per hectare, in kg CO2eq (Opposite of gross GHG emissions per ha). [a, c]	-3,539.75	1,386.20	-6,479.32	-945.42
Economic Performance per Ha	Economic Performance per hectare, in € (Gross profit per ha). [b]	997.15	488.60	-119.23	2,080.15
Labor Use per cow	Number of persons working on the farm, owner included, divided by the herd size. [a]	0.03	0.01	0.01	0.11
Fuel per Ha	Fuel consumption per hectare per year in liter.[a]	67.50	35.28	9.91	185.24
Electricity per cow	Electricity consumption per cow per year in Kwh.[a]	366.10	179.49	84.88	1,030.07
Concentrate per cow	Concentrate feed bought per year in kg.[a]	988.23	360.33	0.00	2,081.81
Share protein in the diet	Share of protein matter in cows' diet.[a]	0.14	0.01	0.12	0.18
Share grass in the diet	Share of grass in the diet.[a]	0.01	0.02	0.00	0.09
Share hay in the diet	Share of hay in the diet.[a]	0.96	0.06	0.78	1.00
Age first calving	Age of the cows when they give birth to their first calf and start producing milk, in months.[a]	32.13	2.96	26	36
Stocking rate	Number of cow per hectare.[a]	0.81	0.26	0.31	1.41
Herd Renewal Rate	Ratio of the number of cows on the number of heifer, proxy for the renewal rate of the herd.[a]	0.31	0.09	0.00	0.60
Ecological Focus Area	Amount of Ecological Focus Area [a, d]	3.24	2.02	0.19	10.17
Farm size	Number of cows. [a]	91.81	50.93	18.61	249.00
Mineral N spread on pasture	Amount of mineral Nitrogen spread per ha and per year on pastures, in N unit.[a]	13.89	15.28	0.00	65.25
Mineral N spread on cereals	Amount of mineral Nitrogen spread per ha and per year on cropland, in N unit.[a]	38.91	59.61	0.00	224.00
Organic N on pasture	Amount of organic fertilizers (manure, slurry) per ha and per year on pastures in N unit.[a]	73.68	26.50	23.99	156.74
Organic N spread on cereals	Amount of organic fertilizers (manure, slurry) spread per ha and per year on cropland, in N unit.[a]	3.93	7.14	0.00	29.05
Mineral P spread on pasture	Amount of mineral Phosphorus spread per ha and per year on pastures, in N unit.[a]	5.16	8.60	0.00	44.00

Mineral P spread on cereals	Amount of mineral Phosphorus spread per ha and per year on cropland, in N unit.[a]	7.65	20.86	0.00	110.00
Mineral K spread on pasture	Amount of mineral Potassium spread per ha and per year on pastures, in N unit.[a]	6.60	10.96	0.00	62.60
Mineral K spread on cereals	Amount of mineral Potassium spread per ha and per year on cropland, in N unit.[a]	8.83	25.14	0.00	119.00
Share manure in organic fertilizers	Share on manure over the total organic fertilizers spread.[a]	0.47	0.08	0.23	0.68
Manure Composing	The farm practices manure composting or not. [a]	0.32	0.47	0	1
Yields of grass	Yields of grass, ton per hectare. [a]	4.42	1.63	0.93	8.92
Yields of forrage	Yields of forrage, ton per hectare. [a]	2.85	3.38	1.54	16.00
Yields of cereals	Yields of cereals, ton per hectare. [a]	2.28	2.87	0.00	7.90
Share of Cambisol	Share of Cambisol, communal level.	0.49	0.27	0.01	1.00
Share of Podzoluvisol	Share of Podzoluvisol, communal level.	0.00	0.00	0	0
Share of Luvisol	Share of Luvisol, communal level, %	0.19	0.25	0.00	0.70
Average Slope	Average slope, communal level, %	20.30	14.56	0.41	58.75
Rainfall	Annual precipitation, communal level, mm	1,136.75	207.05	418	1,569
Temperature	Annual temperature, communal level, °C	8.38	2.13	0	12

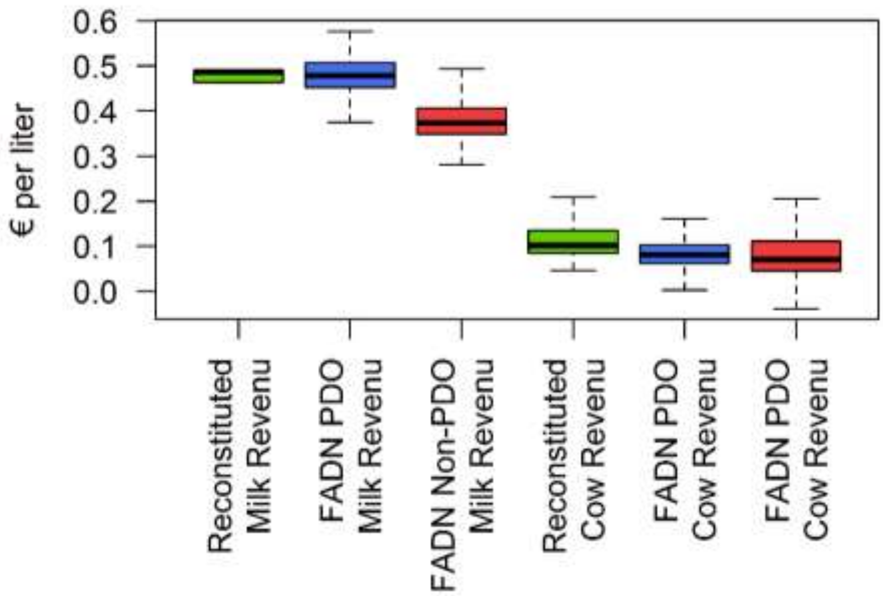
Sources: a. (Institut de L'Elevage, 2013; Michaud, 2016; Perrard, 2016).

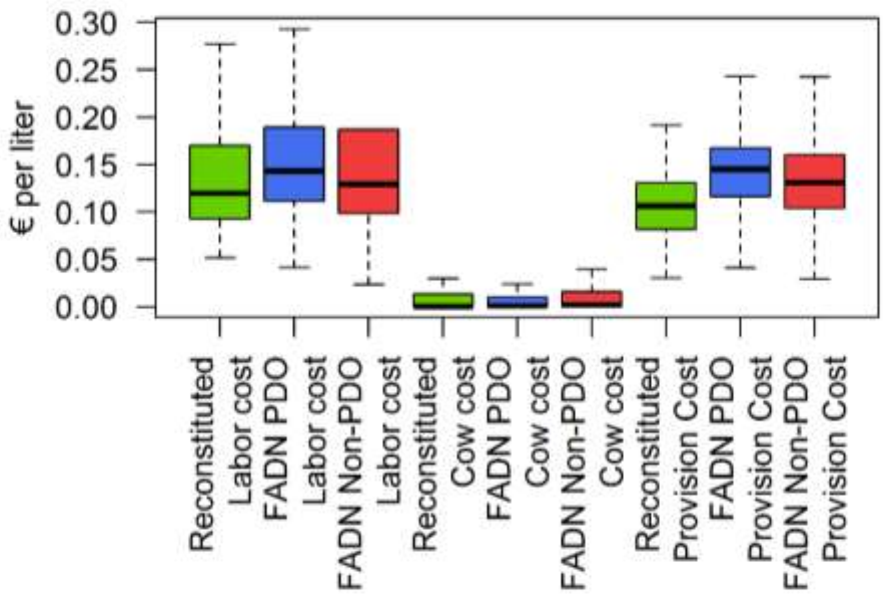
b. FADN; (Ministère de l'Agriculture et de l'Alimentation, 2015a, 2017); (Eurostat, 2017).

c. CAP'2ER (Institut de l'Elevage, 2013).

d. The Ecological Focus Area is computed by aggregating all natural elements creating biodiversity (trees, hedge, terraces, and ponds) after applying a biodiversity coefficient to each type. For example, 1 linear meter of hedge corresponds to 10m² of Ecological Focus Area, while 1m² of pond correspond to 1m² of Ecological Focus Area (Ministère de l'Agriculture et de l'Alimentation, 2015b).

SM 3. Detailed revenue and cost reconstitution





SM 4. Complete OLS results

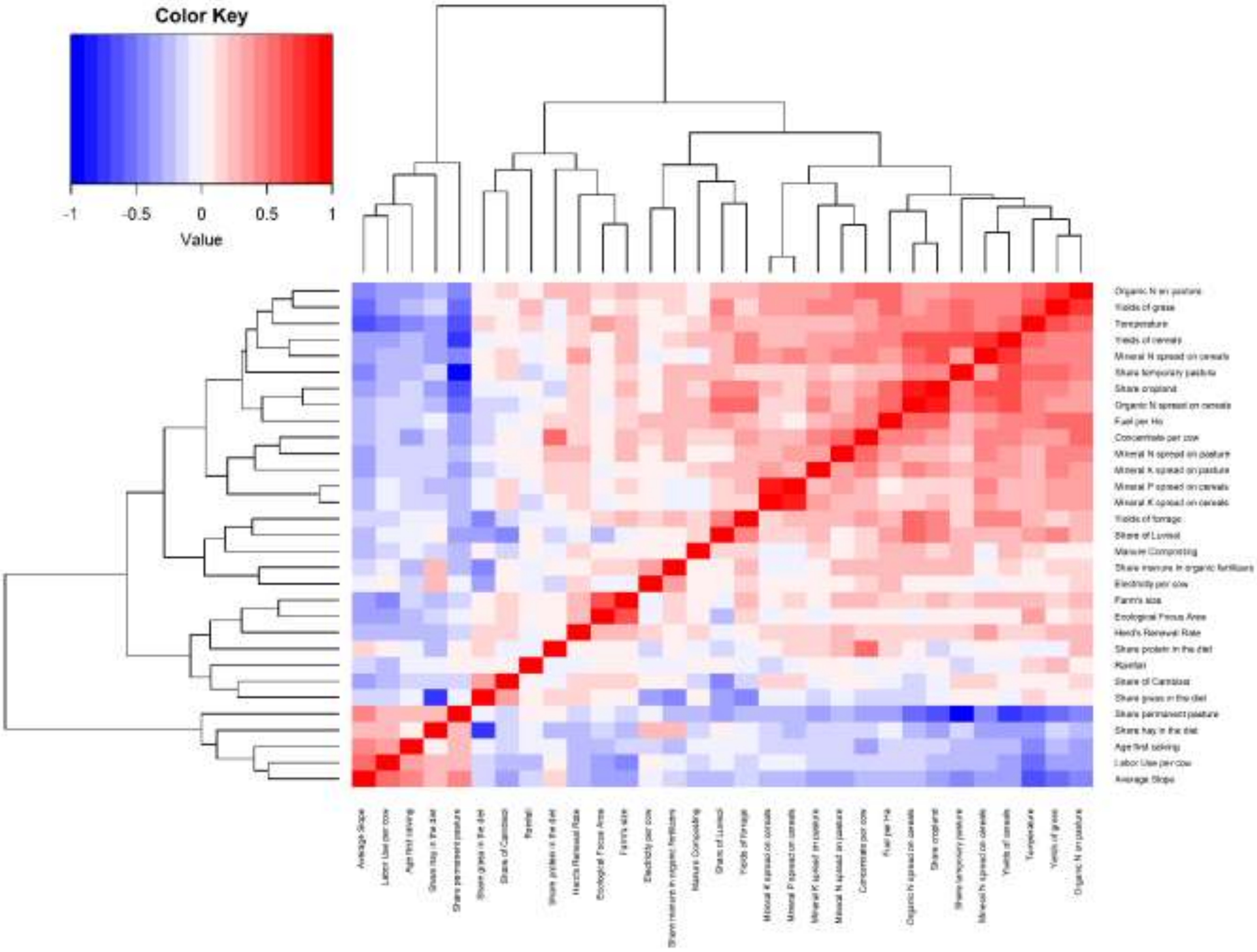
	Net Environmental performance per L (1)	Gross Environmental performance per L (2)	Economic performance per L (3)	Net Environmental performance per Ha (4)	Gross Environmental performance per Ha (5)	Economic performance per Ha (6)
Labor Use per cow	-5.00	-1.04	-6.08***	1,745.81	6,819.09	-15,319.7***
	(3.38)	(2.24)	(0.70)	(11,773.86)	(5,484.13)	(2,878.36)
Fuel per Ha	-0.002*	-0.001	0.0002	-4.31	-5.22***	0.61
	(0.001)	(0.001)	(0.0002)	(4.15)	(1.93)	(1.01)
Electricity per cow	0.0004**	0.0003**	-0.0000	-0.03	-0.54*	0.17
	(0.0002)	(0.0001)	(0.0000)	(0.67)	(0.31)	(0.16)
Concentrate per cow	-0.0000	0.0000	-0.0000	-0.14	-0.42*	0.02
	(0.0001)	(0.0001)	(0.0000)	(0.46)	(0.21)	(0.11)
Share protein in the diet	3.50	-1.91	-2.91***	2,058.35	-5,106.24	-8,415.21**
	(3.99)	(2.64)	(0.83)	(13,888.51)	(6,469.11)	(3,395.33)
Share grass in the diet	-0.004	-0.002	0.0002	8.48	12.12	-7.58
	(0.01)	(0.01)	(0.002)	(28.57)	(13.31)	(6.98)
Share hay in the diet	-0.002	-0.002	-0.001	10.87	6.35	-8.58
	(0.01)	(0.01)	(0.002)	(27.10)	(12.62)	(6.63)
Age first calving	-0.01	0.01	0.003	-22.89	-1.11	8.17
	(0.01)	(0.01)	(0.003)	(42.06)	(19.59)	(10.28)
Herd Renewal Rate	-0.26	-0.30	0.003	338.87	-241.20	58.94
	(0.36)	(0.24)	(0.07)	(1,254.81)	(584.48)	(306.76)
Ecological Focus Area	-0.0001	-0.0002	-0.0001**	0.69	-0.17	-0.43**
	(0.0002)	(0.0001)	(0.0000)	(0.69)	(0.32)	(0.17)
Farm size	-0.001	-0.0001	0.0001	-1.64	0.78	0.29
	(0.001)	(0.001)	(0.0002)	(2.96)	(1.38)	(0.72)
Mineral N spread on pasture	0.003	-0.0002	0.0001	-14.56	-19.47***	6.68***
	(0.003)	(0.002)	(0.001)	(9.10)	(4.24)	(2.23)
Mineral N spread on cereals	-0.001	-0.0001	-0.0001	-1.89	-0.45	-0.40
	(0.001)	(0.0005)	(0.0001)	(2.49)	(1.16)	(0.61)
Organic N on pasture	-0.004**	0.0005	0.0000	-38.55***	-32.19***	7.57***
	(0.002)	(0.001)	(0.0003)	(5.81)	(2.71)	(1.42)
Organic N spread on cereals	-0.003	0.001	0.001	-1.28	14.40	1.59
	(0.01)	(0.005)	(0.001)	(24.51)	(11.42)	(5.99)
Mineral P spread on pasture	-0.003	0.004	0.001	-15.15	1.86	3.70
	(0.005)	(0.003)	(0.001)	(16.25)	(7.57)	(3.97)
Mineral K spread on pasture	-0.001	-0.002	-0.001	-4.31	-1.82	-4.56
	(0.004)	(0.002)	(0.001)	(13.03)	(6.07)	(3.19)
Mineral K spread on cereals	0.001	0.0004	0.0002	0.79	-1.22	1.76
	(0.001)	(0.001)	(0.0003)	(4.59)	(2.14)	(1.12)
Share manure in organic fertilizers	-0.69	-0.08	0.01	-3,593.83**	-305.90	222.04
	(0.49)	(0.32)	(0.10)	(1,705.98)	(794.63)	(417.06)
Manure Composting	-0.14**	-0.09**	-0.01	-306.13	-84.75	-97.04*
	(0.07)	(0.04)	(0.01)	(235.60)	(109.74)	(57.60)
Share of Cambisol	-0.28**	-0.05	-0.01	-837.91*	-76.30	-138.32

	(0.14)	(0.09)	(0.03)	(476.74)	(222.06)	(116.55)
Share of Luvisol	0.31	0.05	-0.004	-197.33	-347.88	94.57
	(0.21)	(0.14)	(0.04)	(721.91)	(336.26)	(176.49)
Average Slope	-0.002	-0.002	-0.001	1.65	6.38	-6.09**
	(0.004)	(0.002)	(0.001)	(12.25)	(5.71)	(3.00)
Year 2014	0.25*	0.05	0.07**	466.74	-216.89	265.60**
	(0.15)	(0.10)	(0.03)	(519.56)	(242.01)	(127.02)
Year 2015	0.23**	0.03	0.08***	385.91	-123.96	334.65***
	(0.10)	(0.07)	(0.02)	(364.97)	(170.00)	(89.23)
Rainfall	0.0001	-0.0001	0.0000	0.93*	-0.35	-0.17
	(0.0002)	(0.0001)	(0.0000)	(0.55)	(0.26)	(0.14)
Temperature	-0.14***	-0.01	0.001	-286.19***	49.36	-16.25
	(0.03)	(0.02)	(0.01)	(101.57)	(47.31)	(24.83)
Constant	1.01	-0.53	0.81***	2,645.66	-43.49	2,579.30**
	(1.23)	(0.81)	(0.25)	(4,267.82)	(1,987.90)	(1,043.36)
Observations	95	95	95	95	95	95
R^2	0.75	0.35	0.82	0.87	0.94	0.86
Adjusted R^2	0.65	0.09	0.75	0.81	0.91	0.80

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

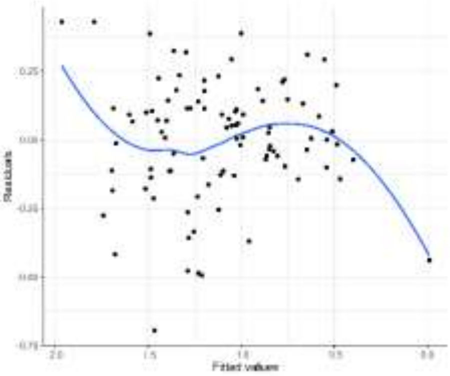
SM 5. Correlation Matrix of the explanatory variables

Correlation Matrix of the explanatory variables

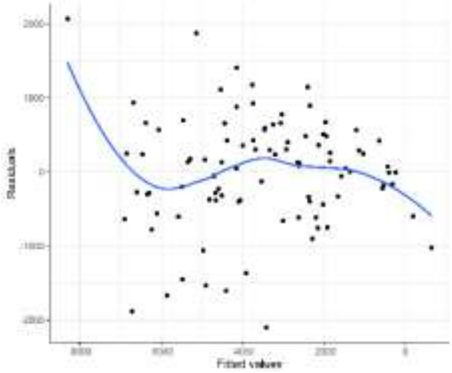


SM 6. Heteroscedasticity correction Check of the OLS model

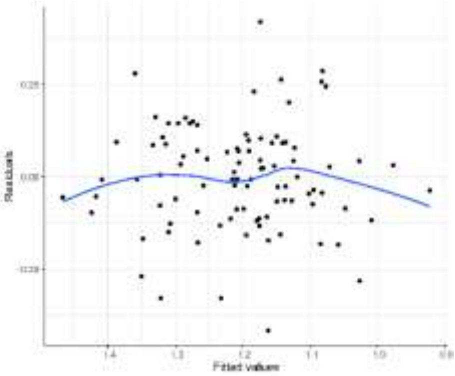
Residual vs fitted values' plot for Model 1



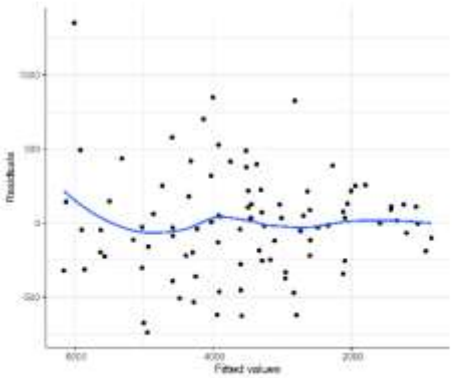
Residual vs fitted values' plot for Model 4



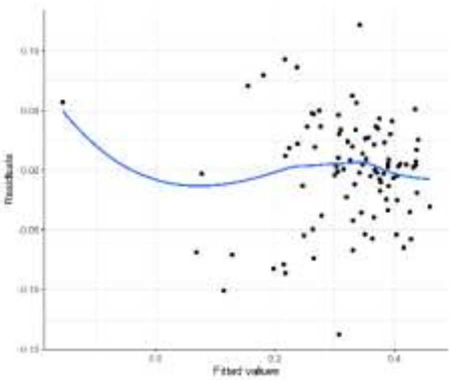
Residual vs fitted values' plot for Model 2



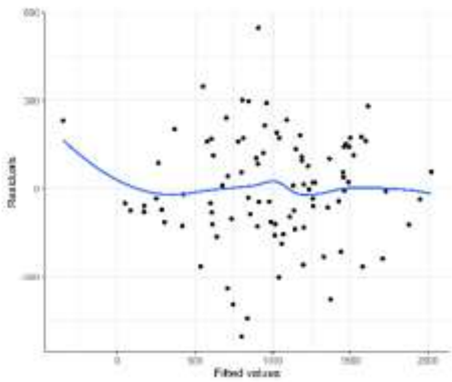
Residual vs fitted values' plot for Model 5



Residual vs fitted values' plot for Model 3



Residual vs fitted values' plot for Model 6



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

	Net Environmental performance per L (1)	Gross Environmental performance per L (2)	Economic performance per L (3)	Net Environmental performance per Ha (4)	Gross Environmental performance per Ha (5)	Economic performance per Ha (6)
Labor Use per cow	-7.21	-2.47	-6.08***	-42.63	6,518.86	-15,319.70***
	(4.41)	(2.99)	(0.70)	(13,602.61)	(5,457.78)	(2,878.36)
Fuel per Ha	-0.003*	-0.001	0.0002	-6.02	-6.79***	0.61
	(0.002)	(0.001)	(0.0002)	(4.79)	(1.92)	(1.01)
Electricity per cow	0.001**	0.0004**	-0.0000	0.10	-0.62**	0.17
	(0.0002)	(0.0002)	(0.0000)	(0.77)	(0.31)	(0.16)
Concentrate per cow	0.0000	0.0001	-0.0000	0.02	-0.35	0.02
	(0.0002)	(0.0001)	(0.0000)	(0.53)	(0.21)	(0.11)
Share protein in the diet	5.95	-0.59	-2.91***	6,254.37	-4,081.04	-8,415.21**
	(5.20)	(3.53)	(0.83)	(16,045.71)	(6,438.03)	(3,395.33)
Share grass in the diet	-0.004	-0.0005	0.0002	4.44	10.27	-7.58
	(0.01)	(0.01)	(0.002)	(33.00)	(13.24)	(6.98)
Share hay in the diet	-0.003	-0.002	-0.001	5.39	1.68	-8.58
	(0.01)	(0.01)	(0.002)	(31.31)	(12.56)	(6.63)
Age first calving	-0.02	0.005	0.003	-40.69	-12.71	8.17
	(0.02)	(0.01)	(0.003)	(48.59)	(19.50)	(10.28)
Herd Renewal Rate	-0.60	-0.56*	0.003	-266.71	-806.63	58.94
	(0.47)	(0.32)	(0.07)	(1,449.71)	(581.67)	(306.76)
Ecological Focus Area	-0.0001	-0.0002	-0.0001**	0.88	-0.13	-0.43**
	(0.0003)	(0.0002)	(0.0000)	(0.80)	(0.32)	(0.17)
Farm size	-0.001	-0.0003	0.0001	-1.76	0.97	0.29
	(0.001)	(0.001)	(0.0002)	(3.42)	(1.37)	(0.72)
Mineral N spread on pasture	0.004	0.0002	0.0001	-15.95	-22.43***	6.68***
	(0.003)	(0.002)	(0.001)	(10.52)	(4.22)	(2.23)
Mineral N spread on cereals	-0.0000	0.0004	-0.0001	-0.79	0.64	-0.40
	(0.001)	(0.001)	(0.0001)	(2.88)	(1.16)	(0.61)
Organic N on pasture	-0.005**	0.0003	0.0000	-48.76***	-40.88***	7.57***
	(0.002)	(0.001)	(0.0003)	(6.72)	(2.69)	(1.42)
Organic N spread on cereals	-0.01	-0.002	0.001	-8.81	12.19	1.59
	(0.01)	(0.01)	(0.001)	(28.32)	(11.36)	(5.99)
Mineral P spread on pasture	-0.005	0.004	0.001	-20.52	0.65	3.70
	(0.01)	(0.004)	(0.001)	(18.78)	(7.53)	(3.97)
Mineral K spread on pasture	-0.001	-0.002	-0.001	-6.56	-2.67	-4.56
	(0.005)	(0.003)	(0.001)	(15.06)	(6.04)	(3.19)
Mineral K spread on cereals	0.001	0.0003	0.0002	0.02	-2.36	1.76
	(0.002)	(0.001)	(0.0003)	(5.30)	(2.13)	(1.12)
Share manure in organic fertilizers	-0.54	0.39	0.01	-3,881.26*	384.25	222.04
	(0.64)	(0.43)	(0.10)	(1,970.96)	(790.81)	(417.06)
Manure composting	-0.16*	-0.10*	-0.01	-318.37	-75.90	-97.04*
	(0.09)	(0.06)	(0.01)	(272.19)	(109.21)	(57.60)
Share of Cambisol	-0.33*	-0.07	-0.01	-971.54*	-114.34	-138.32

	(0.18)	(0.12)	(0.03)	(550.79)	(220.99)	(116.55)
Share of Luvisol	0.34	0.05	-0.004	-483.26	-678.24**	94.57
	(0.27)	(0.18)	(0.04)	(834.04)	(334.64)	(176.49)
Average Slope	-0.004	-0.01*	-0.001	-5.36	-0.93	-6.09**
	(0.005)	(0.003)	(0.001)	(14.16)	(5.68)	(3.00)
Year 2014	0.29	0.10	0.07**	434.54	-298.46	265.60**
	(0.19)	(0.13)	(0.03)	(600.26)	(240.84)	(127.02)
Year 2015	0.34**	0.14	0.08***	540.41	-49.06	334.65***
	(0.14)	(0.09)	(0.02)	(421.66)	(169.18)	(89.23)
Rainfall	0.0002	0.0001	0.0000	1.16*	-0.22	-0.17
	(0.0002)	(0.0001)	(0.0000)	(0.64)	(0.26)	(0.14)
Temperature	-0.19***	-0.02	0.001	-388.64***	25.89	-16.25
	(0.04)	(0.03)	(0.01)	(117.35)	(47.08)	(24.83)
Constant	1.01	-1.34	0.81***	4,129.21	504.55	2,579.30**
	(1.60)	(1.09)	(0.25)	(4,930.71)	(1,978.35)	(1,043.36)
Observations	95	95	95	95	95	95
R^2	0.71	0.35	0.82	0.88	0.95	0.86
Adjusted R^2	0.60	0.09	0.75	0.83	0.93	0.80

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

SM 8. Sensitivity Analysis: changing the LCA perimeter

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

	Net Environmental performance per L (1)	Gross Environmental performance per L (2)	Economic performance per L (3)	Net Environmental performance per Ha (4)	Gross Environmental performance per Ha (5)	Economic performance per Ha (6)
Labor Use per cow	-7.08**	-3.12	-6.08***	-1,428.72	3,644.56	-15,319.70***
	(3.34)	(2.49)	(0.70)	(11,738.04)	(6,336.61)	(2,878.36)
Fuel per Ha	-0.002	-0.001	0.0002	-4.47	-5.39**	0.61
	(0.001)	(0.001)	(0.0002)	(4.13)	(2.23)	(1.01)
Electricity per cow	0.0004**	0.0002	-0.0000	-0.54	-1.05***	0.17
	(0.0002)	(0.0001)	(0.0000)	(0.67)	(0.36)	(0.16)
Concentrate per cow	-0.0001	-0.0001	-0.0000	-0.51	-0.79***	0.02
	(0.0001)	(0.0001)	(0.0000)	(0.46)	(0.25)	(0.11)
Share protein in the diet	-2.50	-7.90***	-2.91***	-12,795.90	-19,960.49***	-8,415.21**
	(3.94)	(2.94)	(0.83)	(13,846.26)	(7,474.70)	(3,395.33)
Share grass in the diet	-0.001	0.001	0.0002	22.00	25.64*	-7.58
	(0.01)	(0.01)	(0.002)	(28.48)	(15.37)	(6.98)
Share hay in the diet	-0.0003	-0.0003	-0.001	19.89	15.37	-8.58
	(0.01)	(0.01)	(0.002)	(27.02)	(14.58)	(6.63)
Age first calving	-0.01	0.004	0.003	-28.97	-7.19	8.17
	(0.01)	(0.01)	(0.003)	(41.93)	(22.64)	(10.28)
Herd Renewal Rate	-0.48	-0.51*	0.003	295.07	-285.00	58.94
	(0.36)	(0.27)	(0.07)	(1,250.99)	(675.33)	(306.76)
Ecological Focus Area	-0.0001	-0.0002	-0.0001**	0.57	-0.29	-0.43**
	(0.0002)	(0.0001)	(0.0000)	(0.69)	(0.37)	(0.17)
Farm size	-0.0004	0.0002	0.0001	-0.33	2.09	0.29
	(0.001)	(0.001)	(0.0002)	(2.95)	(1.59)	(0.72)
Mineral N spread on pasture	0.002	-0.002	0.0001	-21.76**	-26.66***	6.68***
	(0.003)	(0.002)	(0.001)	(9.08)	(4.90)	(2.23)
Mineral N spread on cereals	-0.0001	0.0003	-0.0001	-0.64	0.80	-0.40
	(0.001)	(0.001)	(0.0001)	(2.49)	(1.34)	(0.61)
Organic N on pasture	-0.003**	0.001	0.0000	-45.00***	-38.65***	7.57***
	(0.002)	(0.001)	(0.0003)	(5.80)	(3.13)	(1.42)
Organic N spread on cereals	0.0002	0.004	0.001	9.17	24.86*	1.59
	(0.01)	(0.01)	(0.001)	(24.44)	(13.19)	(5.99)
Mineral P spread on pasture	-0.002	0.005	0.001	-12.19	4.82	3.70
	(0.005)	(0.003)	(0.001)	(16.20)	(8.75)	(3.97)
Mineral K spread on pasture	-0.001	-0.001	-0.001	-3.89	-1.40	-4.56
	(0.004)	(0.003)	(0.001)	(12.99)	(7.01)	(3.19)
Mineral K spread on cereals	0.001	0.0004	0.0002	-0.33	-2.35	1.76
	(0.001)	(0.001)	(0.0003)	(4.57)	(2.47)	(1.12)
Share manure in organic fertilizers	-0.59	0.02	0.01	-3,006.53*	281.41	222.04
	(0.48)	(0.36)	(0.10)	(1,700.79)	(918.15)	(417.06)
Manure Composting	-0.15**	-0.10*	-0.01	-306.01	-84.62	-97.04*
	(0.07)	(0.05)	(0.01)	(234.88)	(126.80)	(57.60)

Share of Cambisol	-0.34**	-0.12	-0.01	-919.79*	-158.18	-138.32
	(0.14)	(0.10)	(0.03)	(475.29)	(256.58)	(116.55)
Share of Luvisol	0.24	-0.01	-0.004	-458.03	-608.58	94.57
	(0.20)	(0.15)	(0.04)	(719.72)	(388.53)	(176.49)
Average Slope	-0.004	-0.004	-0.001	-1.15	3.58	-6.09**
	(0.003)	(0.003)	(0.001)	(12.22)	(6.59)	(3.00)
Year 2014	0.25*	0.05	0.07**	419.99	-263.65	265.60**
	(0.15)	(0.11)	(0.03)	(517.98)	(279.63)	(127.02)
Year 2015	0.28***	0.08	0.08***	399.49	-110.38	334.65***
	(0.10)	(0.08)	(0.02)	(363.86)	(196.43)	(89.23)
Rainfall	0.0003	0.0000	0.0000	1.08*	-0.20	-0.17
	(0.0002)	(0.0001)	(0.0000)	(0.55)	(0.30)	(0.14)
Temperature	-0.14***	-0.01	0.001	-268.17**	67.38	-16.25
	(0.03)	(0.02)	(0.01)	(101.26)	(54.67)	(24.83)
Constant	1.43	-0.11	0.81***	3,728.14	1,038.99	2,579.30**
	(1.21)	(0.90)	(0.25)	(4,254.84)	(2,296.91)	(1,043.36)
Observations	95	95	95	95	95	95
R^2	0.72	0.47	0.82	0.89	0.94	0.86
Adjusted R^2	0.61	0.26	0.75	0.85	0.92	0.80

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

SM 9. Sensitivity Analysis: accounting for the impact of management practices on carbon sequestration

	Net Environmental performance per L (1)	Gross Environmental performance per L (2)	Economic performance per L (3)	Net Environmental performance per Ha (4)	Gross Environmental performance per Ha (5)	Economic performance per Ha (6)
Labor Use per cow	-8.22**	-1.04	-6.08***	-4,422.44	6,819.09	-15,319.70***
	(3.82)	(2.24)	(0.70)	(11,278.95)	(5,484.13)	(2,878.36)
Fuel per Ha	-0.001	-0.001	0.0002	-4.50	-5.22***	0.61
	(0.001)	(0.001)	(0.0002)	(3.97)	(1.93)	(1.01)
Electricity per cow	0.001**	0.0003**	-0.0000	0.18	-0.54*	0.17
	(0.0002)	(0.0001)	(0.0000)	(0.64)	(0.31)	(0.16)
Concentrate per cow	-0.0000	0.0000	-0.0000	-0.46	-0.42*	0.02
	(0.0001)	(0.0001)	(0.0000)	(0.44)	(0.21)	(0.11)
Share protein in the diet	7.54*	-1.91	-2.91***	12,473.64	-5,106.24	-8,415.21**
	(4.50)	(2.64)	(0.83)	(13,304.71)	(6,469.11)	(3,395.33)
Share grass in the diet	0.005	-0.002	0.0002	39.48	12.12	-7.58
	(0.01)	(0.01)	(0.002)	(27.37)	(13.31)	(6.98)
Share hay in the diet	-0.001	-0.002	-0.001	14.87	6.35	-8.58
	(0.01)	(0.01)	(0.002)	(25.96)	(12.62)	(6.63)
Age first calving	-0.02*	0.01	0.003	-83.01**	-1.11	8.17
	(0.01)	(0.01)	(0.003)	(40.29)	(19.59)	(10.28)
Herd Renewal Rate	-0.38	-0.30	0.003	-312.01	-241.20	58.94
	(0.41)	(0.24)	(0.07)	(1,202.07)	(584.48)	(306.76)
Ecological Focus Area	0.0001	-0.0002	-0.0001**	1.23*	-0.17	-0.43**
	(0.0002)	(0.0001)	(0.0000)	(0.66)	(0.32)	(0.17)
Farm size	-0.0003	-0.0001	0.0001	0.35	0.78	0.29
	(0.001)	(0.001)	(0.0002)	(2.84)	(1.38)	(0.72)
Mineral N spread on pasture	0.01*	-0.0002	0.0001	-2.81	-19.47***	6.68***
	(0.003)	(0.002)	(0.001)	(8.72)	(4.24)	(2.23)
Mineral N spread on cereals	-0.0003	-0.0001	-0.0001	-0.61	-0.45	-0.40
	(0.001)	(0.0005)	(0.0001)	(2.39)	(1.16)	(0.61)
Organic N on pasture	-0.003	0.0005	0.0000	-41.49***	-32.19***	7.57***
	(0.002)	(0.001)	(0.0003)	(5.57)	(2.71)	(1.42)
Organic N spread on cereals	-0.01	0.001	0.001	-19.38	14.40	1.59
	(0.01)	(0.005)	(0.001)	(23.48)	(11.42)	(5.99)
Mineral P spread on pasture	-0.004	0.004	0.001	-21.30	1.86	3.70
	(0.01)	(0.003)	(0.001)	(15.57)	(7.57)	(3.97)
Mineral K spread on pasture	-0.001	-0.002	-0.001	0.69	-1.82	-4.56
	(0.004)	(0.002)	(0.001)	(12.48)	(6.07)	(3.19)
Mineral K spread on cereals	0.0003	0.0004	0.0002	-1.31	-1.22	1.76
	(0.001)	(0.001)	(0.0003)	(4.39)	(2.14)	(1.12)
Share manure in organic fertilizers	-0.52	-0.08	0.01	-2,737.76*	-305.90	222.04
	(0.55)	(0.32)	(0.10)	(1,634.27)	(794.63)	(417.06)
Manure Composting	-0.07	-0.09**	-0.01	-97.83	-84.75	-97.04*

	(0.08)	(0.04)	(0.01)	(225.69)	(109.74)	(57.60)
Share of Cambisol	-0.14	-0.05	-0.01	-665.29	-76.30	-138.32
	(0.15)	(0.09)	(0.03)	(456.70)	(222.06)	(116.55)
Share of Luvisol	0.50**	0.05	-0.004	370.53	-347.88	94.57
	(0.23)	(0.14)	(0.04)	(691.57)	(336.26)	(176.49)
Average Slope	-0.004	-0.002	-0.001	-4.04	6.38	-6.09**
	(0.004)	(0.002)	(0.001)	(11.74)	(5.71)	(3.00)
Year 2014	0.25	0.05	0.07**	258.25	-216.89	265.60**
	(0.17)	(0.10)	(0.03)	(497.72)	(242.01)	(127.02)
Year 2015	0.16	0.03	0.08***	45.04	-123.96	334.65***
	(0.12)	(0.07)	(0.02)	(349.63)	(170.00)	(89.23)
Rainfall	0.0001	-0.0001	0.0000	0.43	-0.35	-0.17
	(0.0002)	(0.0001)	(0.0000)	(0.53)	(0.26)	(0.14)
Temperature	-0.10***	-0.01	0.001	-221.89**	49.36	-16.25
	(0.03)	(0.02)	(0.01)	(97.30)	(47.31)	(24.83)
Constant	-0.22	-0.53	0.81***	1,453.74	-43.49	2,579.30**
	(1.38)	(0.81)	(0.25)	(4,088.43)	(1,987.90)	(1,043.36)
Observations	95	95	95	95	95	95
R^2	0.50	0.35	0.82	0.85	0.94	0.86
Adjusted R^2	0.30	0.09	0.75	0.79	0.91	0.80

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

SM 10. Sensibility Analysis: accounting for indirect land-use changes (upper-bound estimate of iLUC effect)

	Net Environmental performance per L (1)	Gross Environmental performance per L (2)	Economic performance per L (3)	Net Environmental performance per Ha (4)	Gross Environmental performance per Ha (5)	Economic performance per Ha (6)
Labor Use per cow	25.08	-1.04	-6.08***	24,218.63	6,819.09	-15,319.70***
	(23.31)	(2.24)	(0.70)	(44,896.55)	(5,484.13)	(2,878.36)
Fuel per Ha	0.01	-0.001	0.0002	-2.44	-5.22***	0.61
	(0.01)	(0.001)	(0.0002)	(15.81)	(1.93)	(1.01)
Electricity per cow	-0.0000	0.0003**	-0.0000	-1.41	-0.54*	0.17
	(0.001)	(0.0001)	(0.0000)	(2.54)	(0.31)	(0.16)
Concentrate per cow	0.001	0.0000	-0.0000	-1.01	-0.42*	0.02
	(0.001)	(0.0001)	(0.0000)	(1.74)	(0.21)	(0.11)
Share protein in the diet	-37.39	-1.91	-2.91***	-36,921.72	-5,106.24	-8,415.21**
	(27.50)	(2.64)	(0.83)	(52,960.21)	(6,469.11)	(3,395.33)
Share grass in the diet	-0.01	-0.002	0.0002	-31.26	12.12	-7.58
	(0.06)	(0.01)	(0.002)	(108.93)	(13.31)	(6.98)
Share hay in the diet	-0.02	-0.002	-0.001	-73.91	6.35	-8.58
	(0.05)	(0.01)	(0.002)	(103.34)	(12.62)	(6.63)
Age first calving	0.09	0.01	0.003	12.79	-1.11	8.17
	(0.08)	(0.01)	(0.003)	(160.39)	(19.59)	(10.28)
Herd Renewal Rate	-0.66	-0.30	0.003	-5,490.30	-241.20	58.94
	(2.48)	(0.24)	(0.07)	(4,784.90)	(584.48)	(306.76)
Ecological Focus Area	0.0005	-0.0002	-0.0001**	-2.85	-0.17	-0.43**
	(0.001)	(0.0001)	(0.0000)	(2.64)	(0.32)	(0.17)
Farm size	0.002	-0.0001	0.0001	11.79	0.78	0.29
	(0.01)	(0.001)	(0.0002)	(11.29)	(1.38)	(0.72)
Mineral N spread on pasture	-0.02	-0.0002	0.0001	-45.80	-19.47***	6.68***
	(0.02)	(0.002)	(0.001)	(34.72)	(4.24)	(2.23)
Mineral N spread on cereals	0.002	-0.0001	-0.0001	8.81	-0.45	-0.40
	(0.005)	(0.0005)	(0.0001)	(9.51)	(1.16)	(0.61)
Organic N on pasture	0.03**	0.0005	0.0000	-0.89	-32.19***	7.57***
	(0.01)	(0.001)	(0.0003)	(22.17)	(2.71)	(1.42)
Organic N spread on cereals	0.02	0.001	0.001	123.63	14.40	1.59
	(0.05)	(0.005)	(0.001)	(93.46)	(11.42)	(5.99)
Mineral P spread on pasture	0.05	0.004	0.001	110.32*	1.86	3.70
	(0.03)	(0.003)	(0.001)	(61.98)	(7.57)	(3.97)
Mineral K spread on pasture	-0.03	-0.002	-0.001	-63.91	-1.82	-4.56
	(0.03)	(0.002)	(0.001)	(49.69)	(6.07)	(3.19)
Mineral K spread on cereals	-0.001	0.0004	0.0002	-2.14	-1.22	1.76
	(0.01)	(0.001)	(0.0003)	(17.49)	(2.14)	(1.12)
Share manure in organic fertilizers	-0.13	-0.08	0.01	6,831.58	-305.90	222.04
	(3.38)	(0.32)	(0.10)	(6,505.31)	(794.63)	(417.06)
Manure Composting	0.19	-0.09**	-0.01	1,070.51	-84.75	-97.04*

	(0.47)	(0.04)	(0.01)	(898.38)	(109.74)	(57.60)
Share of Cambisol	1.09	-0.05	-0.01	3,691.97**	-76.30	-138.32
	(0.94)	(0.09)	(0.03)	(1,817.92)	(222.06)	(116.55)
Share of Luvisol	-2.04	0.05	-0.004	-2,770.03	-347.88	94.57
	(1.43)	(0.14)	(0.04)	(2,752.83)	(336.26)	(176.49)
Average Slope	-0.01	-0.002	-0.001	6.75	6.38	-6.09**
	(0.02)	(0.002)	(0.001)	(46.72)	(5.71)	(3.00)
Year 2014	-0.77	0.05	0.07**	-2,828.05	-216.89	265.60**
	(1.03)	(0.10)	(0.03)	(1,981.22)	(242.01)	(127.02)
Year 2015	-0.97	0.03	0.08***	-2,393.36*	-123.96	334.65***
	(0.72)	(0.07)	(0.02)	(1,391.73)	(170.00)	(89.23)
Rainfall	-0.001	-0.0001	0.0000	-5.66***	-0.35	-0.17
	(0.001)	(0.0001)	(0.0000)	(2.11)	(0.26)	(0.14)
Temperature	0.70***	-0.01	0.001	1,437.10***	49.36	-16.25
	(0.20)	(0.02)	(0.01)	(387.33)	(47.31)	(24.83)
Constant	-7.57	-0.53	0.81***	-1,108.96	-43.49	2,579.30**
	(8.45)	(0.81)	(0.25)	(16,274.23)	(1,987.90)	(1,043.36)
Observations	95	95	95	95	95	95
R^2	0.67	0.35	0.82	0.58	0.94	0.86
Adjusted R^2	0.53	0.09	0.75	0.41	0.91	0.80

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

SM 11. Interaction effects

	Net Environmental performance per L (1)	Gross Environmental performance per L (2)	Economic performance per L (3)	Net Environmental performance per Ha (4)	Gross Environmental performance per Ha (5)	Economic performance per Ha (6)
Electricity per cow	-0.001	-0.001	-0.0003	-2.68	-1.43	0.04
	(0.001)	(0.001)	(0.0002)	(3.87)	(1.81)	(0.92)
Share hay in the diet	-0.01	-0.01	-0.003	-16.56	-2.59	-11.93
	(0.01)	(0.01)	(0.003)	(43.77)	(20.43)	(10.42)
Fuel per ha	0.001	-0.001	0.002	6.15	-0.96	-0.05
	(0.01)	(0.004)	(0.001)	(23.13)	(10.80)	(5.51)
Share grass in the diet	0.06	-0.04	0.001	394.16**	151.98*	-63.65
	(0.05)	(0.03)	(0.01)	(179.97)	(84.02)	(42.85)
Concentrates	0.0001	-0.0003	-0.0001	1.43	0.43	-0.48
	(0.001)	(0.0004)	(0.0001)	(1.94)	(0.91)	(0.46)
Labor Use per cow	-4.43	-2.12	-6.43***	1,415.10	5,683.35	-17,635.98***
	(3.64)	(2.33)	(0.72)	(12,341.19)	(5,761.38)	(2,938.55)
Share protein in the diet	3.25	-1.10	-2.74***	2,826.73	-3,911.25	-7,089.72**
	(4.18)	(2.68)	(0.82)	(14,191.77)	(6,625.30)	(3,379.19)
Age first calving	-0.02	0.01	0.004	-58.13	-10.62	16.61
	(0.01)	(0.01)	(0.003)	(46.25)	(21.59)	(11.01)
Herd Renewal Rate	-0.20	-0.22	0.02	388.22	-302.58	75.16
	(0.38)	(0.24)	(0.07)	(1,286.06)	(600.39)	(306.22)
Ecological Focus Area	-0.0002	-0.0001	-0.0001	0.30	-0.17	-0.32*
	(0.0002)	(0.0001)	(0.0000)	(0.78)	(0.36)	(0.19)
Farm size	-0.0005	-0.0004	0.0000	0.18	1.09	-0.13
	(0.001)	(0.001)	(0.0002)	(3.27)	(1.52)	(0.78)
Mineral N spread on pasture	0.001	0.01*	0.01**	8.16	5.72	29.66***
	(0.01)	(0.01)	(0.002)	(36.23)	(16.92)	(8.63)
Mineral N spread on cereals	-0.001	-0.0001	-0.0001	-1.95	-0.25	-0.32
	(0.001)	(0.0005)	(0.0001)	(2.55)	(1.19)	(0.61)
Organic N on pasture	-0.005**	0.001	0.0003	-40.09***	-31.26***	9.50***
	(0.002)	(0.001)	(0.0004)	(6.51)	(3.04)	(1.55)
Organic N spread on cereals	-0.0002	0.001	0.002	16.44	22.11*	1.87
	(0.01)	(0.005)	(0.002)	(25.97)	(12.12)	(6.18)
Mineral P spread on pasture	-0.002	0.003	0.0002	-11.86	1.54	1.81
	(0.005)	(0.003)	(0.001)	(16.66)	(7.78)	(3.97)
Mineral K spread on pasture	-0.002	-0.001	-0.001	-11.29	-3.93	-3.78
	(0.004)	(0.003)	(0.001)	(13.46)	(6.29)	(3.21)
Mineral K spread on cereals	0.001	0.001	0.0005	3.21	0.77	2.95**
	(0.001)	(0.001)	(0.0003)	(5.07)	(2.36)	(1.21)
Share manure in organic fertilizers	-0.67	0.05	0.05	-3,877.95**	-342.16	329.02
	(0.52)	(0.33)	(0.10)	(1,747.42)	(815.77)	(416.08)
Manure Composting	-0.17**	-0.09**	-0.02	-390.50	-109.48	-79.66
	(0.07)	(0.05)	(0.01)	(249.88)	(116.66)	(59.50)
Share of Cambisol	-0.26*	-0.04	-0.02	-758.66	-71.84	-151.14
	(0.15)	(0.09)	(0.03)	(501.37)	(234.06)	(119.38)
Share of Luvisol	0.27	0.11	0.02	-227.83	-280.80	213.23
	(0.22)	(0.14)	(0.04)	(737.92)	(344.49)	(175.71)
Average Slope	-0.002	-0.002	-0.001	-1.24	5.94	-5.43*
	(0.004)	(0.002)	(0.001)	(12.37)	(5.78)	(2.95)

Year dummy 2015	0.26	-0.003	0.04	385.26	-349.35	167.88
	(0.16)	(0.10)	(0.03)	(551.91)	(257.65)	(131.41)
Year dummy 2014	0.24**	0.05	0.08***	336.80	-173.07	342.95***
	(0.11)	(0.07)	(0.02)	(381.09)	(177.91)	(90.74)
Rainfall	0.0001	-0.0001	0.0000	0.93	-0.30	-0.14
	(0.0002)	(0.0001)	(0.0000)	(0.58)	(0.27)	(0.14)
Temperature	-0.13***	-0.02	-0.001	-267.05**	45.59	-31.96
	(0.03)	(0.02)	(0.01)	(103.69)	(48.41)	(24.69)
Electricity: Share hay in the diet	0.0000	0.0000	0.0000	0.05	0.02	0.003
	(0.0000)	(0.0000)	(0.0000)	(0.07)	(0.03)	(0.02)
Fuel: Share grass in the diet	-0.0001	-0.0000	-0.0000	-0.21	-0.10	-0.003
	(0.0001)	(0.0001)	(0.0000)	(0.48)	(0.22)	(0.11)
Share grass diet: Concentrates	-0.0000	0.0000	0.0000	-0.03	-0.02	0.01
	(0.0000)	(0.0000)	(0.0000)	(0.04)	(0.02)	(0.01)
Mineral N pasture: Organic N pasture	0.0000	-0.0001*	-0.0001**	-0.30	-0.29	-0.25***
	(0.0001)	(0.0001)	(0.0000)	(0.39)	(0.18)	(0.09)
Share grass diet^2	-0.001	0.0003	0.0000	-3.68**	-1.21	0.49
	(0.0005)	(0.0003)	(0.0001)	(1.65)	(0.77)	(0.39)
Constant	0.13	0.58	0.80**	-4,699.65	-3,326.82	3,823.52**
	(1.93)	(1.24)	(0.38)	(6,558.34)	(3,061.71)	(1,561.60)
Observation	95	95	95	95	95	95
R^2	0.76	0.41	0.85	0.88	0.94	0.88
Adjusted R^2	0.63	0.11	0.77	0.82	0.91	0.81

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

SM 12. Variables Selection via LASSO

	Net Environmental performance per L (1)	Gross Environmental performance per L (2)	Economic performance per L (3)	Net Environmental performance per Ha (4)	Gross Environmental performance per Ha (5)	Economic performance per Ha (6)
Labor Use per cow	-0.002**	-0.001**		-13.87	-4.08***	
	(0.001)	(0.001)		(16.82)	(1.47)	
Fuel per Ha	0.0004**	0.0003***			-0.49*	0.21
	(0.0002)	(0.0001)			(0.25)	(0.14)
Electricity per cow					-0.41***	
					(0.15)	
Concentrate per cow			-6.05***		4,109.13	-14,379.54***
			(0.56)		(3,951.77)	(2,436.57)
Share protein in the diet	-0.004		0.0001		8.99	
	(0.004)		(0.001)		(5.84)	
Share grass in the diet			-0.001			
			(0.001)			
Share hay in the diet		-1.64	-2.65***			-7,963.99***
		(1.88)	(0.61)			(2,786.09)
Age first calving		0.003	0.003			
		(0.01)	(0.002)			
Herd Renewal Rate	-0.19	-0.30				
	(0.33)	(0.19)				
Biodiversity	-0.001					
	(0.001)					
Farm size	-0.0003			-12.49		
	(0.001)			(9.84)		
Mineral N spread on pasture					-20.33***	7.81***
					(3.36)	(1.80)
Mineral N spread on cereals	-0.002			-64.08***	-33.05***	7.45***
	(0.001)			(23.42)	(2.21)	(1.15)
Organic N on pasture	-0.003			-163.28*		1.08
	(0.01)			(94.57)		(4.05)
Organic N spread on cereals	-0.58			-5,952.18		260.84
	(0.43)			(6,297.74)		(337.23)
Mineral P spread on pasture		-0.0001	-0.0001**			-0.29**
		(0.0001)	(0.0000)			(0.11)
Mineral K spread on pasture		0.003		-81.24		
		(0.002)		(59.05)		
Mineral K spread on cereals		0.0005				1.36
		(0.001)				(0.99)
Share manure in organic fertilizers	-0.15**	-0.08**		-1,687.80		-56.43
	(0.06)	(0.04)		(1,025.86)		(49.84)
Manure Composting	-0.32***			-4,475.44***		
	(0.11)			(1,683.44)		
Share of Cambisol			-0.0005			

			(0.001)			
Share of Luvisol	0.15		0.07^{**}			203.80^{*}
	(0.13)		(0.03)			(108.74)
Average Slope	0.17^{**}		0.08^{***}			282.21^{***}
	(0.08)		(0.02)			(62.01)
Year 2014	-0.10^{***}		0.001	$-1,119.65^{***}$		
	(0.02)		(0.005)	(287.85)		
Year 2015		0.11	0.02			248.34^{**}
		(0.08)	(0.03)			(118.40)
Rainfall		-0.0001		5.14^{**}	-0.29	-0.16
		(0.0001)		(2.22)	(0.20)	(0.12)
Temperature			-0.001		6.42^{*}	-2.33
			(0.001)		(3.55)	(2.27)
Constant	0.62^{*}	-0.85^{**}	0.77^{***}	$13,482.89^{***}$	-319.73	$1,679.41^{***}$
	(0.35)	(0.36)	(0.18)	(4,177.03)	(486.53)	(448.22)
Observations	95	95	95	95	95	95
R^2	0.70	0.33	0.81	0.68	0.93	0.84
Adjusted R^2	0.65	0.24	0.79	0.64	0.92	0.81

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

Chapter 2

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

Note: This chapter is based on paper currently submitted to the Environmental and Resources Economics under the same title, coauthored with Stéphane De Cara, Catherine Brocas and Valentin Bellassen.

2.0. Abstract

There is a lack of clear empirical evidence towards the lower carbon footprint of organic products, in particular in the dairy sector. Until now, comparisons of organic and conventional food have been hindered by small sample sizes, lack of properly defined counterfactual and the omission of land-use related emissions. Here we bridge these gaps by mobilizing a uniquely large dataset of 3,191 French dairy farms. We find that the carbon footprint of organic milk is 29% (95%*CI* = [16% - 41%]) lower than its conventional counterpart without indirect land-use change and 8.6% (95%*CI* = [0.02% - 15%]) lower with indirect land use changes, without compromising economic performance. In both production systems, farms' profitability is similar and associated with a higher carbon footprint. These findings are robust to a variety of assumptions and are likely to hold for meat production. They support the inclusion of organic farming in climate mitigation levers.

Keywords: *Organic; greenhouse gas emissions; gross margin; dairy farms; land use changes.*

2.1. Introduction

Promoting extensive farming systems, and in particular organic ones, has been presented as a sustainable direction to limit greenhouse gases emissions (GHGE) and other environmental externalities in recent public policies, such as the European Union's "Farm to Fork Strategy" (European Commission, 2020). 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 and Wachter, 2016). However, lower average yields in organic systems (Seufert et al., 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). Clear and thorough assessments of the environmental performances of organic farming - especially in comparison to conventional farming systems - are thus needed to determine whether organic farming is actually a way to mitigate climate change. The stakes are particularly high for the livestock sector which accounts for 14-24% of global GHGE and 80% of the GHGE of the agricultural sector (Rogissart et al., 2019). In France, farm emissions (including land-use changes) from the livestock sector are estimated at around 19% of the territorial GHGE emissions (Ministère de la Transition Ecologique et Solidaire, 2018).

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 (Bellassen et al., 2021; Cederberg and Mattsson, 2000; Haas et al., 2001; Kristensen et al., 2011; Stonehouse et al., 2001; Thomassen et al., 2008; van der Werf et al., 2009). 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. Meta-analyses, the typical tools to overcome small sample sizes in individual studies, also came up with conflicting results (Clark and Tilman, 2017; Mondelaers et al., 2009; Tuomisto et al., 2012) 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 (Froehlich et al., 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 livestock (Rogissart et al., 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 and 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 cropland into grassland or hedges – which may offset indirect land-use changes. Moreover, these models rely on many assumptions and interactions which 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 reaches 3,191 LCAs of dairy farms in France, among which 72 are organic, that is almost 40 times more the largest dataset used in past studies. 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 strengthen the causal inference on the differences found between organic and conventional farms. 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 29% (95%*CI* = [16% - 41%]) lower than its conventional counterpart without indirect land-use change and 8.6% (95%*CI* = [0.02% - 15%]) lower with indirect land use changes.

In addition, we estimate the difference in economic performance between organic and conventional farms, using their gross operating margin. 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 et al., 2019).

The literature on the economic performances of organic and conventional farms is also substantial but suffers from the same pitfalls as LCAs, i.e. small sample sizes and lack of robust selection of counterfactuals. Crowder and Reganold (2015) review 129 studies that compare the economic performance of organic and conventional farming, and find that, thanks 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 yields higher revenue per liter of milk produced as well as lower production costs (European Commission, 2013; Sanders et al., 2016). In this study, using propensity score weighting and a large dataset, we uncover that gross margin are not significantly different between organic and conventional farms and thus that organic dairy farming reduces the carbon footprint without compromising farms' economic performances.

2.2. Methodology

2.2.1. Population characterization and notations.

Consider a population of N_i farms (indexed by $i = 1 \ldots N$). 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, labor units (LU)…).

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 (see SI 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, most extensive farms have a deficit in productivity which we account for by considering these farms would have to import 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 products, $E_i + C_i^{dLUC} + C_i^{Pr} + C_i^{iLUC}$, 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 consider the gross margin per labor unit $\frac{\Pi_i}{LU_i}$, that we simply name *Gross Margin*. 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.

2.2.2. 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 et al., 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 gross and LUC-related GHGE are given in SI 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 which 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 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 (Mario Herrero et al., 2013). Note that the choice of the reference farm does impact our results on the relative difference in GHGE between farms within the sample. Carbon fluxes (sequestration or emission) associated to each type of land-use changes include both the actual flux resulting from the change and the alteration of future carbon fluxes implied by the change. For example, a farm which has 100% of pasture on 100 ha of total land is estimated to sequester 3.72 tCO2e ha^{-1} yr^{-1} on the 82 ha which could have been converted to cropland to match the reference farm. The impact of temporary grassland on soil carbon is considered within farming practices (see below). The actual values and their sources are detailed in SI 4.

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 et al., 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 surface of hedges. The carbon impact of these practices follows a temporal pattern similar to the carbon impact of dLUC: a change in practice leads to carbon sequestration or emissions which 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 therefore considered.

Indirect LUC (iLUC) is a more controversial topic and its estimates are laden with high uncertainties. As 82 ha of pasture do not yield as much nutritious capacity for cows as 82 ha of cropland, if feed demand is assumed to be inelastic, a transition from 82 ha of feed crops to 82 ha of pasture will require a complement in concentrates. This rationale is the basis of our method to estimate iLUC: 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 productivity that the observed farm would have had if its share of permanent grassland was the same as the reference farm. In the case of organic farms, which tend to have has less crop area than the reference farm, the iLUC represents the GHGE this farm is responsible for, as it has a lower on-farm nutritional capacity and would need additional concentrates to be as productive as more intensive (conventional) farms. Thus, we include as iLUC the area that is deforested in Brazil to meet the demand of soybean cakes of the observed farm. 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.

2.2.3. Propensity score weighting and average treatment effect

The proper counter-factual environmental and economic performances of the organic farms in our dataset is selected through a propensity score weighting using the package “twang” in R software (Ridgeway et al., 2017). This method proceeds in three steps: firstly, the probability of receiving a treatment, i.e. the propensity score, is estimated using the covariates. Then, weights are computed based on the propensity score and assigned to each individual: the treated individuals have a weight of one, and the control individuals with higher propensity scores have weights closer to one than the control farms with low propensity scores. Finally, a weighted t-test determines the average treatment effect on the treated (ATT). We estimate generalized boosted regression instead of the classical logit regression to compute the propensity score as it handles better non-linearity, skewed distribution and outliers. This is highly relevant in our case as the size of our treatment groups strongly differs 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 (3,000 trees were used 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).

As the treatment we are interested in is being part of an organic farming scheme, we estimate the average treatment effect on the treated (ATT) on the GHGE and gross margin of organic farms compared to their conventional counterparts. The propensity score is based on 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 soil composition as control variables and the set of GHGE and gross margin indicators as variables of interest.

2.3. Data

Our main data source are the field surveys of 3,054 dairy farms in France, once misreported values have been filtered out (SI 4). These surveys 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 and herd 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 variables used in the propensity score weighting model are available in SI 5.

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 SI 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.

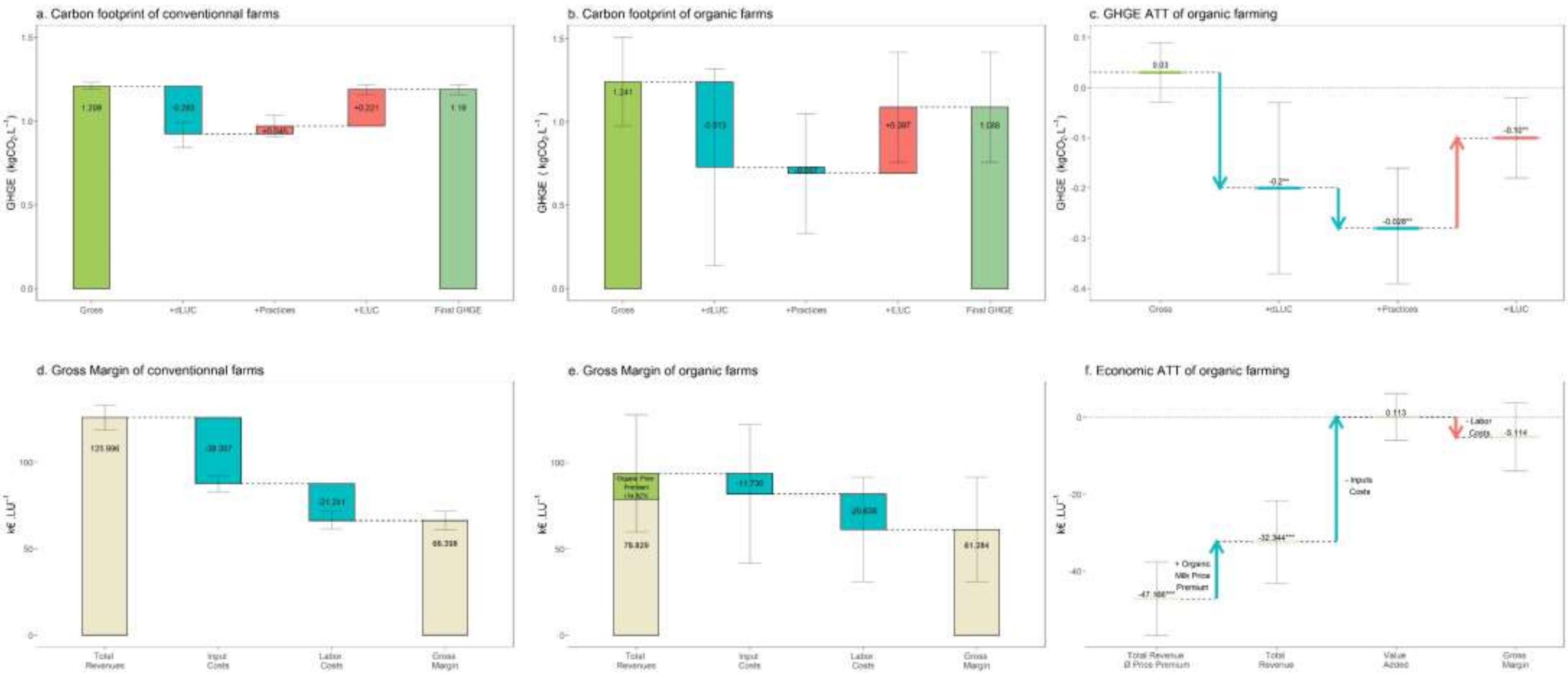
To compute the GHGE related to land-use changes (C_i^{dLUC}, C_i^{Pr} & C_i^{iLUC}), we use the model introduced in section 2.2. and further detailed in SI 2, with the parameters presented in SI 4.

2.4. Results and discussion

2.4.1. The carbon footprint of organic vs conventional farms

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 29% (95%*CI* = [16% - 41%]) lower than its conventional counterparts (Figure 1). Including an estimated of indirect land-use change effects reduces the benefits of organic milk to 8.6% (95%*CI* = [0.02% - 15%]). The results are not dependent on the covariates used in the propensity score estimation as results are similar when farm area and herd size are excluded from the propensity score (Table SI 7a). They are also largely unaffected by the exclusion of outliers in terms of labor units (Table SI 7b) and by controlling for the remaining matching biases (Table SI 6b and SI 3). As expected however, increasing the *transition period* over which the carbon storage and emissions from land-use changes are supposed to happen from the IPCC default of 20 years (IPCC, 2019) to an upper bound of 50 years (Poeplau and Don, 2013) substantially attenuates the benefits of organic milk to 8% (95%*CI* = [3% - 13%]) and 3% (95%*CI* = [-3% - 0.8%]) with indirect LUC (Table SI 7c.).

Figure 1. Decomposition and ATT of carbon footprint and gross margin.



Whiskers indicate standard deviation in frames a, b, c and d and the 95% confidence interval of the ATT in frames e. 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 domestic feed supply. All representations are based of the weighted data.

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 (3%, p-value = 0.328, Figure 1e. & Table SI 7a). Half of the GHGE of dairy farms stem from enteric fermentation, which is decreasing in the cows productivity and in the share of concentrates in cows diet (Zehetmeier et al., 2012). As conventional farms are more productive, mostly because they use more concentrates, their cows emit less methane per unit of product than their organic counterparts which 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. A similar trade-off is identified in a study of 47 French dairy farms (41 conventional and 6 organic) where the difference in gross GHGE is not statistically significant: 1.04 and 1.08 kgCO2e per kg FPCM of milk for conventional and organic farms respectively (van der Werf et al., 2009). More generally, studies in different countries highlight this trade-off, usually resulting in a non-significant differences on the gross carbon footprint of milk (Cederberg and Mattsson, 2000; Haas et al., 2001; Kristensen et al., 2011; Thomassen et al., 2008).

When the carbon consequences of land use changes within the farms (dLUC) are introduced, the carbon footprint of organic milk the turns out to be 21% lower than its conventional counterpart (p-value = 0.0347, Figure 1e. & Table SI 7a). Indeed, organic farms have a much higher share of permanent grassland than their conventional counterpart, and each additional hectare of permanent grassland lowers farm emissions by 3.7 $tCO_2e\ yr^{-1}$ (SM 2). This higher share of permanent grassland – an average 45% of AAU versus 36% for the conventional weighted counterparts – is partly mandated by the technical specifications, 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 difference in carbon footprint is even higher when the impact of key management practices on carbon sequestration is accounted for (29% lower GHGE, p-value = $6.1e^{-06}$, Figure 1e. & Table SI 7a). This is largely driven by a higher share of temporary grassland in crop rotation – an average 71% versus 46% for the conventional weighted counterparts – although total nitrogen fertilization of permanent grassland is lower – 92 $kgN\ ha^{-1}$ versus 183 $kgN\ ha^{-1}$ for the conventional weighted counterparts – and density of hedges is comparable – 83 $m\ ha^{-1}$ versus 108 $m\ ha^{-1}$ for the conventional weighted counterparts.

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 lower yields somewhere generate 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 (eg. 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 narrows down the difference in carbon footprint between organic and conventional milk to 8.6% (p- value = 0.0115, Figure 1e. & Table SI 7a). 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 are assumed to be grown at the expense of South American forests (see SI 2&4 for further details).

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 (see SI 2), the carbon footprint of organic farms can turn out to be either substantially higher than or equal to their conventional counterparts (-34%[1], p-value = $3.69e^{-05}$ and -0.04%, p-value = 0.325 respectively, Table SI 7a).

Our iLUC results differ from other LCA analyses which only include iLUC from soybean cakes' production, as in (Flysjö et al., 2012), (Guerci et al., 2013) or (Hörtenhuber et al., 2010). Indeed, our scope for iLUC is larger as we also include the difference in productivity of organic farming, whose existence implies the intensification of other dairy farms or the extension of agricultural area (Schmidt et al., 2015; Searchinger et al., 2018). Smith et al. (2019) shows that shifting a whole national agricultural sector to organic production has a similar impact when LUC are included: considering only local LUC and carbon sequestration yields a lower carbon footprint for organic farms, while including the international LUC to compensate for the lower productivity of organic farming cancels out this effect. Without the proper selection of counterfactuals (t-test without matching, Table SI 7a.), the estimated difference in carbon footprint with iLUC is slightly lower (-0.06 vs -0.1 $kgCO2e.L^{-1}$) and no longer significantly different from zero (p-value = 0.16).

[1] At the extreme ends of the confidence intervals of the nutritive capacity of maize and grass, grass can turn out to be more nutritive than maize, resulting in an iLUC effect which is favourable to organic milk.

2.4.2. The economic performance of organic vs conventional farms

The economic performance of organic farms - measured as their gross operating margin per labor unit - is not significantly different from their conventional counterparts (-0.08%, p-value = 0.258, Table SI 7a). However, decomposing the gross margin shows that both revenues and inputs costs per labor unit in organic farms are significantly lower than their conventional counterparts (Figure 1c., Figure 1d. & Table SI 7a). Indeed, the 43% smaller production volume of organic farms is not compensated by the 23% average organic price premium and the gross margin of organic farms without the price premium is significantly lower than their conventional counterparts (30%, p-value = $2.73e^{-07}$, Table SI 7a). These lower revenues are however offset by lower costs, thanks to a cheaper feeding strategy which mostly relies on grass and on-farm feed, as mandated by the European organic farming rules (European Commission, 2008). Ultimately, organic farms do not purchase any mineral fertilizers and less off-farm feed, the two main farming expenses of conventional farms (Stonehouse et al., 2001).

This result is somewhat sensitive to the denominator of the economic indicator. Although labor unit is the most common one, economic performance can also be expressed per hectare or per unit of product. Here, the ATT is also not significant for the gross margin per hectare (-0.08%, p-value = 0.186, Table SI 7a), but the gross margin per liter of milk produced is significantly higher for organic farms (48%, p-value = $6.37e^{-14}$, Table SI 7a). 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.

Froehlich et al. (2018) compares the overall profitability of a large sample of Brazilian family farms, using similar robust matching methods and finds that organic farms have a 7-10% smaller overall profit than their conventional counterparts, which could be explained by an average low price premium as only 5% of Brazilian organic farms are certified. Crowder and Reganold (2015) reviews 129 studies that compare the economic performance of organic and conventional crop farming, and finds that organic farms reach a 21% higher gross margin per hectare thanks to the price premium. Their total costs are similar to conventional farms, as higher labor costs are compensated by lower variable costs (fertilizers, pesticides). However, without the price premium, the gross margin per hectare of organic farms is 10% lower. A report on EU crops and animal farming from the European Commission (European Commission, 2013) shows similar descriptive results. Monier-Dilhan et al. (2020) analyze 8 case studies in the EU and conclude that organic products have a median gross operating margin per unit of product 54% higher than their conventional counterparts. Our analysis shows similar results as the gross margin per liter of organic milk is 50% larger than for conventional milk (Table SI 7a.). We also show, as in Crowder and Reganold (2015), that without the organic price premium organic farms would have significantly lower gross margin per labor unit than their conventional counterparts (Table SI 7a.).

2.4.3. Economic vs environmental performances

Figure 2a. Gross margin and Gross GHGE

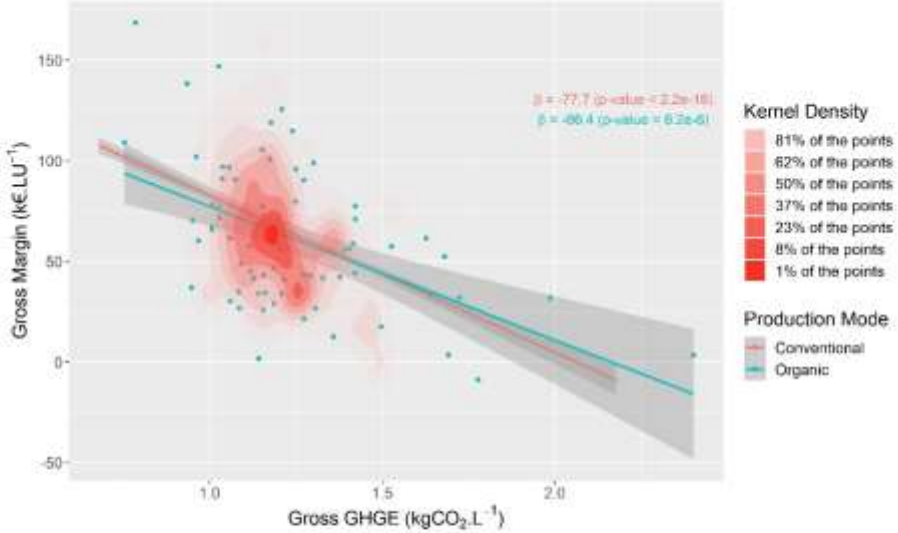


Figure 2b. Gross margin and dLUC GHGE

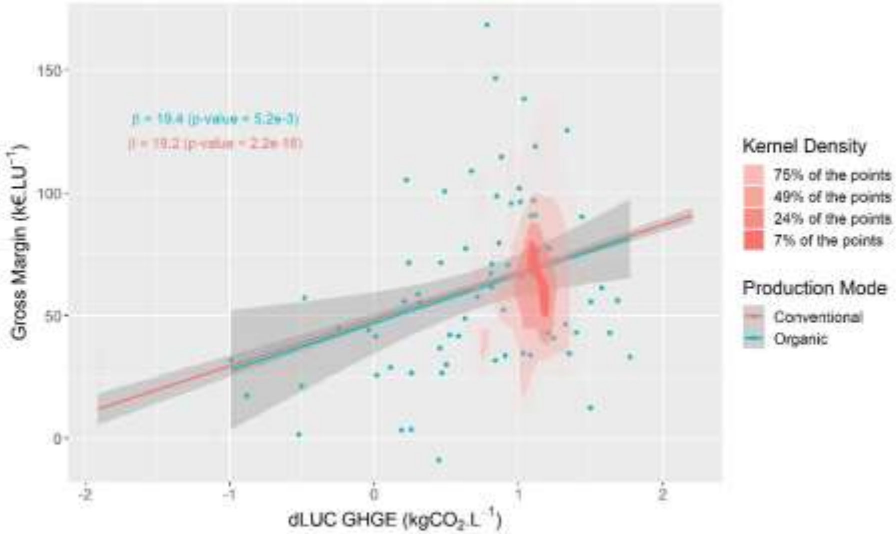


Figure 2c. Gross margin and dLUC GHGE with the impact of practices

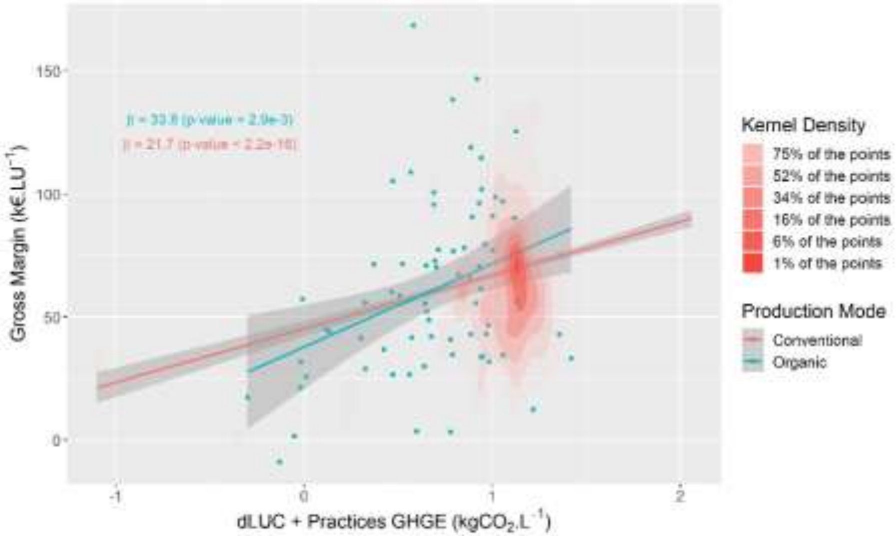
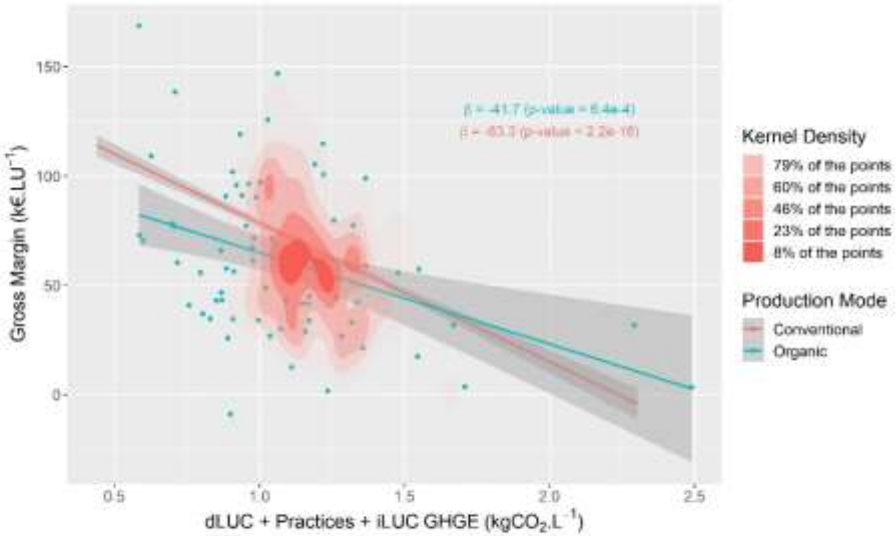


Figure 2d. Gross margin and dLUC + iLUC GHGE with the impact of practices



The most reliable estimate of carbon footprint – gross GHGE + dLUC + practices – is antagonistic to economic performance. In conventional farms, a 1% increase from the average gross margin of 66,398 € LU^{-1} is associated with a 0.2% increase of the carbon footprint (Figure 4c. and SI 8a.). The antagonism is 56% more acute within organic farms and is likely related to the negative correlation (-0.26, p-value $< 2.2e^{-16}$) between cow productivity and grassland area, thus carbon sequestration.

However, economic and environmental performances become slightly synergetic when indirect land-use changes are accounted for (Figure 4d.). Accounting for indirect land-use changes penalizes the less intensive farms, which also tend to be less profitable: the gross margin per labor unit is significantly and positively correlated with all indicators of productivity (Figure SI 8a. and b.). Economic and environmental performances are also synergetic when only gross GHGE are accounted for. Indeed, farms with a larger gross margin per labor unit tend to more efficiently convert feed into milk (Thomassen et al., 2009), resulting in higher cow and acreage productivities (Figure SI 8b.). They also tend to use more concentrates. When carbon sequestration is not accounted for, using a lot of concentrates in feeding strategies also reduces GHGE because of the lower enteric fermentation per liter of milk produced (Lovett et al., 2006). This finding shows that the relationships between economic and environmental performances depends heavily on whether land-use related emissions are accounted for, which confirms similar results obtained in several European countries, although on much smaller sample sizes (Lambotte et al., 2021; O'Brien et al., 2015; Thomassen et al., 2009).

2.4.4. Literature review on the carbon footprint of dairy farms

Table 2. Literature review of relevant articles on the GHGE of dairy farms

Study	Country	Sample Size	Conventional - GHGE per liter	Organic - GHGE per liter	Difference Organic/ Conventional	dLUC	iLUC	Sequestration Practices
(Bonesmo et al., 2013)	Norway	30	1.02					X[2]
(Cederberg and Flysjo, 2004)	Sweden	23	1.04[a]	0.94	-0.1			
(Cederberg and Mattsson, 1999)	Sweden	2	1.1	0.95	-0.15			
(Flysjö et al., 2012)	Sweden	23	1.42	1.23	-0.19	X[2] (Gerber et al. 2010)		
(Flysjö et al., 2012)	Sweden	23	1.21	1.17	-0.04	X[1] (Leip et al. 2010 - medium case)		
(Flysjö et al., 2012)	Sweden	23	1.52	1.26	-0.26	X[1] (Leip et al. 2010 - worst case)		
(Flysjö et al., 2012)	Sweden	23	1.32	1.60	0.28	X (Audsley et al. 2009)		
(Flysjö et al., 2012)	Sweden	23	2.07	2.91	0.86	X (Schmidt et al. 2011)		
(Guerci et al., 2013)	Germany Italy, Denmark	12	1.34[b]	1.26[b]	-0.8	X[1] (Leip et al. 2010 - worst case)		
(Guerci et al., 2013)	Italy	32	1.66			X[1] (Ecoinvent database v.2.0)		
(Guerci et al., 2013)	Italy	32	2.12			X[1] (Gerber et al. 2010)		
(Guerci et al., 2013)	Italy	32	2.58			X[1] (Leip et al. 2010 - worst case)		
(Haas et al., 2001)	Germany	18	1.3	1.3	0			
(Hörtenhuber et al., 2010)	Autria - Alpine	2[c]	1.17	1.02	-0.15	X[1] (only for conventional farms): conversion of savannah to soybean fields		
(Hörtenhuber et al., 2010)	Austria – Upland (pasture)	2[c]	1.03	0.95	-0.08	Same as above		
(Hörtenhuber et al., 2010)	Austria - Upland	2[c]	1.03	0.91	-0.12	Same as above		
(Hörtenhuber et al., 2010)	Austria - lowland	2[c]	0.90	0.81	-0.09	Same as above		
(Kiefer et al., 2014)	Germany	81	1.45	1.61	0.16			
(Kristensen et al., 2011)	Denmark	67	1.20	1.27	0.07			
(O'Brien et al., 2014)	Ireland (pasture)	1[c]	0.84			X[1]		X[2]

[1] All these studies take into account the deforestation associated with soy meals, but neither grassland-related dLUC nor the iLUC associated with differences in feed nutritious content.

[2] All these studies estimate carbon sequestration for stabilized land use, accounting only for the impact of sequestration practices, a method that has been criticized for overestimating real carbon fluxes.

[a] High input farms.

[b] Averaged by the authors.

[c] The farms in each production system are reconstituted from national databases.

(Olesen et al., 2006)	EU	15[c]	1.43	1.57	0.14			
(Schader et al., 2014)	Switzerland	2		0.91				
(Thomassen et al., 2008)	Netherlands	2	1.4	1.5	0.1			
(van der Werf et al., 2009)	France	47	1.04	1.08	0.04			
(Williams et al., 2006)	England & Wales	1[c]	1.06	1.23	0.17			
Total (mean or count)		20.8	1.34	1.27	-0.01	4	0	2

In the literature, organic dairy farms tend to have a higher GHGE than conventional farms when neither LUC or carbon sequestration are accounted for (Table 2), although as mentioned earlier, this evidence cannot be considered as conclusive due to small sample sizes and the lack of an objective counterfactual. Let us note that in these studies, the carbon footprint of organic milk becomes lower than its conventional counterpart when the dLUC associated with soy meals are considered.

The average gross GHGE in our study is within the range in the literature (1.21 and 1.24 $kgCO2e.L^{-1}$ for conventional and organic farms respectively, Table SI 7a., column 1), and particularly close to the findings of Haas et al. (2001) and Kristensen et al. (2011).

We could not find a study comparing conventional and organic dairy system that included an estimate of on-farm carbon sequestration, but O'Brien et al. (2014) in a study of extensive farming use a fixed value of 1.19 $tCO_2eq.yr^{-1}.ha^{-1}$ of grassland which, although very different in principle from our method, ends up conferring a similar relative benefit to organic farms compared with our 3.72 $tCO_2eq.yr^{-1}.ha^{-1}$ of additional grassland. O'Brien et al. (2014) conclude that intensive systems have higher GHGE than extensive ones when carbon sequestration is accounted for, which is consistent with our results with dLUC (Table SI 7a.).

A few studies include the LUC associated with soy meals in Brazil (Flysjö et al., 2012; Guerci et al., 2014; Hörtenhuber et al., 2010). As expected, they find that when the LUC from soy production is accounted for in the LCA of dairy farms, the farms using the most soy meals (conventional farms in those articles, in comparison to organic ones), have a higher carbon footprint. This is again consistent with our dLUC findings. However, our results strongly differ from this conclusion when iLUC are estimated: the farms that use less concentrates and soy meals are less productive and have a higher land occupation, which results in the intensification of other dairy farms and/or the conversion of forest and savannahs in grasslands in our modelling framework. Thus, the lower use of concentrates and lower productivity of organic farms drives up their GHGE through iLUC, offsetting the dLUC benefits from their higher share of grassland in our central estimate (Table SI 7a.).

2.5. 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 9-29% 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 our extraordinary large sample size, the estimated difference in carbon footprint between organic and conventional farms amounts to -39% instead of -29% and the lower end including indirect land-use change is no longer significant (p-value > 0.158). Similarly, a t-test based on simple averages would have led to the erroneous conclusion that conventional farms are significantly more profitable, both in terms of gross margin per hectare and per labor unit. Without accounting for GHGE related to land use 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 triples the difference of carbon footprints between organic and conventional farming, while taking the higher bound halves it, even though the overall effect remains, organic milk has a lower carbon footprint that its conventional counterpart. This uncertainty is one of the arguments against the inclusion biogenic carbon in LCAs. While there is little ground for neglecting direct land use 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, as many others (e.g. Searchinger et al. (2018)), assume that demand is constant. The amount of produce forgone in less productive organic farms must be compensated by an increased production elsewhere. This seems contradictory with the observation that the diet of people consuming more organic products is much more oriented towards vegetal products (Boizot-Szantai et al., 2017; Lacour et al., 2018b), so much that these diets can also have a lower land footprint (Baudry et al., 2019).

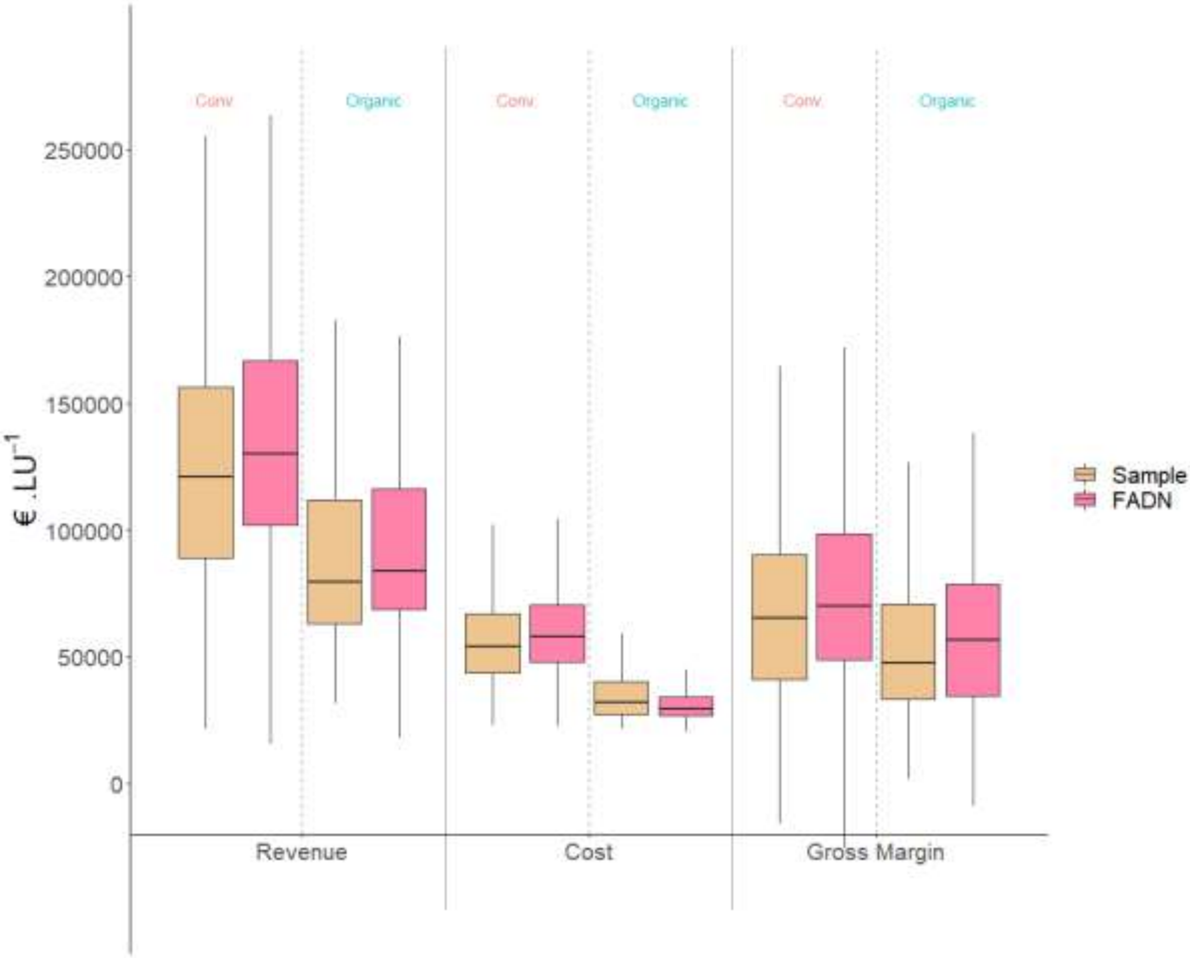
Finally, despite the matching procedure, our results may still be biased by a selection process, as efficient farms are more likely to convert to organic farming (Lansink, 2002; Latruffe and Nauges, 2014). This limit could be overcome with a panel data of farms' LCAs, correcting for the selection bias and furthermore allowing the assessment of GHGE and economic performances before and after the conversion to organic farming. Unfortunately, to the best of our knowledge, this kind of dataset does not exist.

2.6. Supplementary Information

SI 1. Economic performance reconstitution

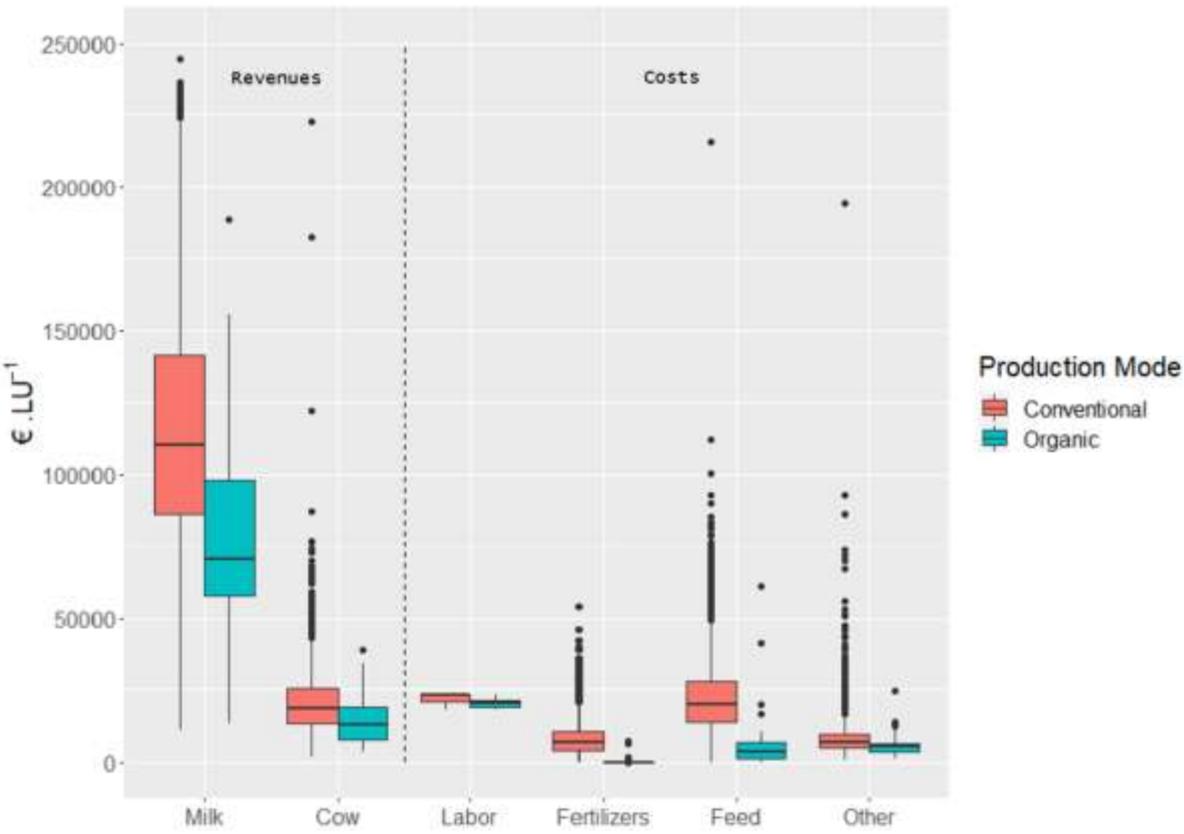
The gross margin Π_i is defined in this study as the difference between the farm's revenue and its costs, without accounting for taxes or subventions. The former includes the revenues from the sale of the farm's outputs O_i : milk, animals (including meat), cereals and roughage. Factor costs include the buying costs of the farm's inputs I_i: forage, concentrates, fertilizer, electricity and fuel, contracted work and animals for the renewal of the herd. Family labor costs are valued at the average wage of paid labor. Gross operating profit (including land leasing charges, taxes and subventions) or current result (including land leasing charges, taxes and subventions, amortization and interests on loans) could not be estimating with our survey data, but in the *Farm Accountancy Data Network* (FADN) both are significantly correlated with our measure of the gross operating margin (73% and 39% respectively).

Figure SI 1a. Reconstitution of cost, revenue and gross margin (in € per labor unit)



The cost, revenue and gross operating margin of the farms in the dataset are well reconstituted when compared with the FADN sample. Overall, organic farms are less profitable than conventional farms (Figure SI 1a). Indeed, even if the price of organic milk is on average 22% higher than the price of conventional milk, organic farms produce less milk. However, the production costs of organic farms are lower, as most of the feed they use is produced on-farm and they do not use fertilizers (Figure SI 1b).

Figure SI 1b. Detailed comparison of revenues and costs (in € per labor unit)



SI 2. Estimation of the environmental performance

Direct LUC

To estimate land-use related emissions and sequestration (Ci), we deviate from CAP'2ER and classical LCAs methodologies. Indeed, CAP'2ER attributes carbon sequestration to static land-uses (acreage of grassland times a fixed carbon sequestration factor) whereas the only stabilized results for cropland and grassland related carbon fluxes in the literature concern land-use changes (LUC). Indeed, the latest IPCC guidelines (IPCC, 2019) estimate carbon fluxes to be null for croplands and grasslands which did not undergo recent land use or management changes. Moreover, the sequestration factor used by CAP'2ER for permanent grassland – 2.09 $tCO2\ ha^{-1}\ yr^{-1}$ – is derived from Soussana et al. (2010) which has been criticized for using a flawed averaging method and for concluding to an average value too large to be consistent with the current knowledge about carbon fluxes and stocks in grassland (Smith, 2014).

Farming practices influencing on-farm carbon sequestration

The share of temporary grasslands in crops rotation, the amount of nitrogen (mineral or organic) fertilization in pastures and the surface of hedges influence significantly the biomass and soil carbon sequestration of dairy farms (Pellerin et al., 2019) and are thus included in our model of dairy farms' GHGE.

Pellerin et al (2019) estimates that 63.7 linear meters of hedges sequesters 29.9 $kgCO2e\ ha^{-1}\ yr^{-1}$ in the soil and biomass on cropland and 28 $kgCO2e\ ha^{-1}\ yr^{-1}$ on pasture, during 50 years. Here, a linear meter of hedge is associated to 2 m² of hedge and 1.5 m² of uncultivated area both side of the hedge. As our dataset only contains the cumulative length of hedges for each farm, we allocate these hedges proportionally to grassland and cropland, based on the land-use of each farm. Emissions or sequestration are then added to the carbon budget of each farm based on the difference with the reference farm for both the amount of hedges in grassland and the amount of hedges in cropland.

Nitrogen fertilization on pasture stimulates the biomass growth and thus soil carbon sequestration. Several reviews conclude that an almost linear relationship exists between nitrogen and carbon sequestration in grasslands, with an average ratio of 1.2 $kgC.kgN^{-1}.yr^{-1}$ for a 20-year horizon (Eze et al., 2018; Fornara et al., 2012; Pellerin et al., 2019). Here again, differences in nitrogen fertilization – both mineral and organic – with the reference farm are translated into carbon emissions or sequestration, using the average ratio above.

The share of temporary pasture in rotation with crops also increases carbon sequestration in soil. For France, Pellerin et al. (2019) estimates that including 50% of temporary pasture in rotation with crops, compared to crops only, sequesters an additional 466 $kgC.ha^{-1}.yr^{-1}$. More generally, the relationship between the annual increase of SOC and the share of temporary pasture in the rotation follows a linear pattern from rotations dominated by cropland (0% of grass) to rotation dominated by grassland (Vertès and Mary, 2007). Accordingly, we assume that soil carbon sequestration and the share of temporary pasture in the rotation are positively and linearly correlated. To be consistent with our LUC estimates, temporary grassland is therefore assumed to increase carbon sequestration by 3.72 tCO2e/% of temporary grassland in the rotation/year during 20 years. For example, as temporary grasslands represent 71% of the UAA (excluding permanent grassland) in the reference farm, a farm with no temporary grassland would be estimated to be emitting 2.6 tCO2e.yr^{-1}.ha^{-1} of UUA excluding permanent pasture, for a 20-year horizon.

Indirect LUC

The quantity of concentrates needed for a given farm to achieve the same nutritious capacity as the reference farm is assumed to stimulate or mitigate deforestation in Brazil as more or less soybeans cake are needed. Indeed, Overmars et al. (2015) shows that 30% of the annual increase of soybean production is meet by the expansion of the area dedicated to soy at the expense of forests and savannas, while the rest is met by yield increases.

Using the formalization of Plevin et al. (2010), our reduced-form models of carbon sequestration or emission from dLUC and iLUC are therefore expressed in equations (1) to (4).

$$LUC_i = \left(share_{grassland_i} - share_{grassland_{ref}}\right) * area_i \tag{1}$$

$$C_i^{dLUC} = LUC_i * \frac{EmissionFactor_{c\to g}^{Fr}}{Period} \tag{2}$$

$$C_i^{iLUC} = LUC_i * DisplacementFactor * \frac{EmissionFactor_{f\to c}^{Br}}{Period} \tag{3}$$

$$\text{where } DisplacementFactor = \frac{(Nutri_C * Yd^C - Nutri_G * Yd^G) * share_{soy}}{Yd_{Br}^{soy} * alloc\_soy * Nutri_{soy}} * area\_expension \tag{4}$$

LUC_i is the difference in grassland are in farm *i* compared to the reference farm in hectares. If a farm is more extensive than the reference farm, LUC_i is positive. $EmissionFactor_{c\to g}^{Fr}$ being negative (Table SI 4b), then C_i^{dLUC} is also negative, and the farm is considered to store carbon from dLUC. The displacement factor (Eq. (4)) is generally positive for extensive farms as the nutritive capacity of one hectare of cropland ($Nutri_C$, the nutritive value of crops in kcal.kg^{-1} multiplied by Yd_i^C the yield of crops in ton.ha^{-1}) is higher than the one of one hectare of grassland ($Nutri_G * Yd_i^G$). $share_{soy}$ is the average share of soybean cakes in the cows' diet, as we consider that only soybean cakes' additional production generates LUC, other additional concentrates and feed entering in the cows' diet in French dairy systems would be produced in France or neighbor countries at the intensive margin, as these countries have stable land use (Taheripour et al., 2017). The nutritional difference between crop and grass x $share_{soy}$ gives the amount of calories that as to be furnished by soy bean cakes. We divide these calories by the $Nutri_{soy}$ (the nutritive values of soy in kcal.kg^{-1}) multiplies by Yd_{Br}^{soy}, the yield of soy in Brazil in ton.ha^{-1}, and $alloc\_soy$, which economically allocates the LUC between soy oil and cakes, both by-products of soybean production. Lastly, we multiply this ratio by $area\_expension$, the area of Brazilian forest and savanna deforested for each addition hectare of soy required. This yields the

$DisplacementFactor$ which indicates how many hectares of forest and savanna are transformed into agricultural land for each hectare of LUC in the French dairy farms. As the $DisplacementFactor$ is generally positive, an extensive farm, with a positive LUC_i is responsible for a positive amount of LUC in Brazil. This area of LUC in Brazil is associated with the emission of GHGE, the carbon released from forest soils, such as $\frac{EmissionFactor_{f\rightarrow c}^{Br}}{Period}$ is also positive. Thus, an extensive farm has a positive C_i^{iLUC}. Yields of crops and grassland are obtained from the sample mean in our dataset and the other parameters are derived from the literature (Table SI 4b). To assess the robustness of our results for different values of the displacement factor, which varies considerably depending on the yields and the values selected for the economic allocation to soybean cakes ($alloc\_soy$) and the area expansion due to increasing soy cultivation, we also compute the bootstrapped 95% confidence interval of the displacement factor based on 95% confidence interval of each parameter (Table SI 4b) and assuming a normal distribution. The 95% confidence interval for the displacement factor is [0.0476; 0.3278] and we use both the inferior and superior bounds of this interval in the estimation of iLUC GHGE as robustness tests. In addition, we compute the different estimates of dLUC, iLUC and the GHGE' impact of sequestration practices with a 50-year period instead of the generic 20-year period.

SI 3. Propensity score weighting and treatment effect

The classic set-up for matching theory, embracing propensity score weighting, referred as Rubin Causal Model (Rubin D. B, 1974), is a sample of N individuals, indexed by $i = 1, \dots, n$, and each individual has two possible outcomes, $Y_i(1)$ and $Y_i(0)$, with or without treatment respectively. The treatment is represented by a dummy t_i, which take the value 1 if the individual received the treatment and 0 otherwise. However, in the sample, each individual only receives the treatment or do not receive it, i.e., we observe only $Y_i^{obs} = \begin{cases} Y_i(1) & if\ t_i = 1 \\ Y_i(0) & if\ t_i = 0 \end{cases}$.

Moreover, for each individual, a matrix X_i, composed of a set of covariates that are not affected by the treatment, is used. Then, the average treatment effect of the population, conditional on the covariates is:

$$\tau(x) = \mathbb{E}[Y_i(1) - Y_i(0)|X_i = x], \tag{4}$$

and the average treatment effect on the treated (ATT) of the population is:

$$\tau_{treat}(x) = \mathbb{E}[Y_i(1) - Y_i(0)|X_i = x, t_i = 1]. \tag{5}$$

As we only observe a sample of the population, the average treatment effect of the sample, conditional on the covariates is:

$\tau_{sample}(x) = \frac{1}{N}\sum_{i=1}^{N} \tau(X_i)$ and the ATT of the sample is $\tau_{treat,sample}(x) = \frac{1}{N_t}\sum_{i:W_i=1}^{N_t} \tau(X_i)$ (6)

Furthermore, two key assumptions are needed to be able to make causal inferences about the ATT, conditional independence of the treatment assignment and common support. Conditional independence is defined as $t_i \perp (Y_i(0), Y_i(1)) \mid X_i$, i.e., for individuals with the same given covariates' values, the potential outcomes are independent of treatment assignment. This can be assessed after the weighting procedure by checking that weighting efficiently balanced the covariates between the individuals who received the treatment and the others. Common support is assumed to forbid perfect predictability of t_i given the covariates X_i, $0 < \mathbb{E}[t_i| X_i = x] < 1$, where the propensity score is

$$e_i(X_i) = \mathbb{E}[t_i| X_i = x] = Pr(t_i = 1| X_i = x). \tag{7}$$

Using the propensity scores, weights can be created for each observed individuals, so that the control individuals that have the most similar features with the treated individuals are assigned the largest weights. Let's call $f(X|t = 1)$ the distribution of the covariates in the treated individuals and $f(X|t = 0)$ in the control individuals. Then, the weights $w(X)$ are constructed such that

$$f(X|t = 1) = w(X)f(X|t = 0) \tag{8}$$

Solving (8) for $w(X)$ and applying the Bayes theorem yields

$$w(X) = K\frac{f(t = 1|X)}{f(t = 0|X)} = K\frac{Pr(t = 1|X)}{1-Pr(t = 1|X)} \tag{9}$$

where K is a normalization constant that cancels out in the estimation of the ATT.

To ensure that as much bias as possible is eliminated by the weighting procedure, we also provide bias-corrected ATT estimates (Abadie et al., 2002), which adjust the ATT estimation by accounting for the remaining differences of covariates between the two groups. Propensity score weighting thus corrects the bias created by variables influencing both the probability of being treated and the ATT (Rosenbaum and Rubin, 1983).

Bias-corrected ATT estimates and other sensitivity tests are provided in the Supplementary Information 6 (Tables SI 6a. & 6b.), evaluating the presence of hidden bias in the propensity score estimation (McCaffrey et al., 2004; Ridgeway, 2006). Hidden bias arises when an unobserved variable (not included in the propensity score estimation) influences the probability of being treated $e_i(x_i)$. The method proposed here is akin to the Rosenbaum bounds (Rosenbaum, 2002) and estimates by how much the treatment effect would change if we account for an unobservable variable z, so that the new weights assigned to individuals based on the propensity score are $w_i(x_i, z_i)$. By setting $a_i = \frac{w_i(x_i,z_i)}{w_i(x_i)}$, we can choose any value of a_i to simulate different strength of hidden bias. If $a_i$is correlated with the outcome of interest, the ATT estimates will vary, and this variation will increase as the correlation is stronger. Thus, the sensibility test gives information on the maximum correlation we could allow between the effect of an unoversable variable on the propensity score weighting, a_i, and the outcome of interest, before the ATT estimate changes. More precisely, we compute “break even” correlations, the value of the correlation between a_i and the outcome of interest that would cancel the ATT. If such break even correlation is low, it would indicate that our propensity score model may be easily biased by any omitted variable slightly correlated with the outcome of interest.

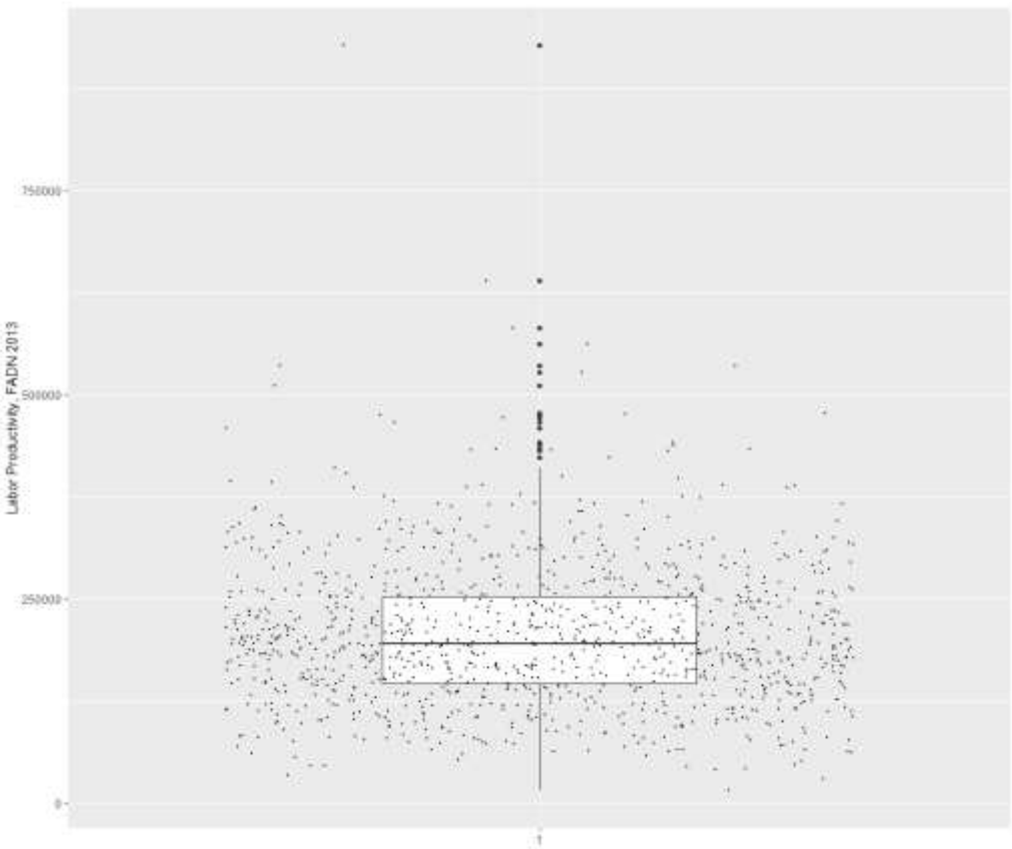
SI 4. Data

Table SI 4. Specification of the carbon sequestration models

Emission factor cropland to grassland in France ($\boldsymbol{EmissionFactor^{Fr}_{c \to g}}$)	-74.3 $tCO2eq.ha^{-1}$ (negative emissions correspond to net carbon storage)	(EFESE, 2019)
Emission factor of LUC in Brazil for soy production ($\boldsymbol{EmissionFactor^{Br}_{soy}}$)	297 $tCO2eq.ha^{-1}$	(Overmars et al., 2015) using the Cropland Spatial Allocation Model (Hiederer et al., 2010).
Nutritious content (*Nutri*)	$Nutri_C$ = 3840 $kcal.kg^{-1}$ $Nutri_G$ = 4010 $kcal.\ kg^{-1}$ $Nutri_{soy.}$ = 4090 $kcal.\ kg^{-1}$	feedtables.com
Yield (*Yd*, $t.ha^{-1}$)	Yd^C=13.77 , Yd^G= 6.1, $Yd^{soy}_{Br} = 2.45$	Own data (sample average of forrage corn for Yd^C and grazed grass for Yd^G) and Overmars et al. (2015) for Yd^{soy}_{Br}.
Share soy cake in concentrates (share_soy)	0.29*0.45 (share cakes in concentrates * share soy in cakes) = 0.13	(Ministère de l'Agriculture et de l'Alimentation, 2017)
Economic allocation for soy cakes	0.57	(Overmars et al., 2015)
Area expansion for increasing soy demand (area_expansion)	0.3	(Overmars et al., 2015)
Displacement Factor (*DisplacementFactor*)	0.194 [-0.04; 0.25]	Authors' calculation based on equation 3
Production Period (*Period*)	20 year	Default transition period in (IPCC, 2019).

As any field survey, our data suffers from misreporting, especially for labor which is reputedly subject to misreporting in the agricultural sector (Midler et al., 2019). Indeed, some farms declare a low number of labor units, relatively to their milk production. To determine which farms are actual cases of misreporting, we use the 2013 FADN sample and extract the minimum and maximum labor productivity (milk production in liter divided by labor units used). We excluded the extreme maximum visible in Figure SI 4, such that the minimum and maximum labor productivities reach 14,354 and 638,471 $L.LU^{-1}$ respectively. We remove from our dataset the farms for which the labor productivity falls outside this range, i.e. 137 conventional farms for the rest of the analysis.

Figure SI 4. Distribution of the labor productivity from the 2013 FADN



SI 5. Summary statistics and description of the variables

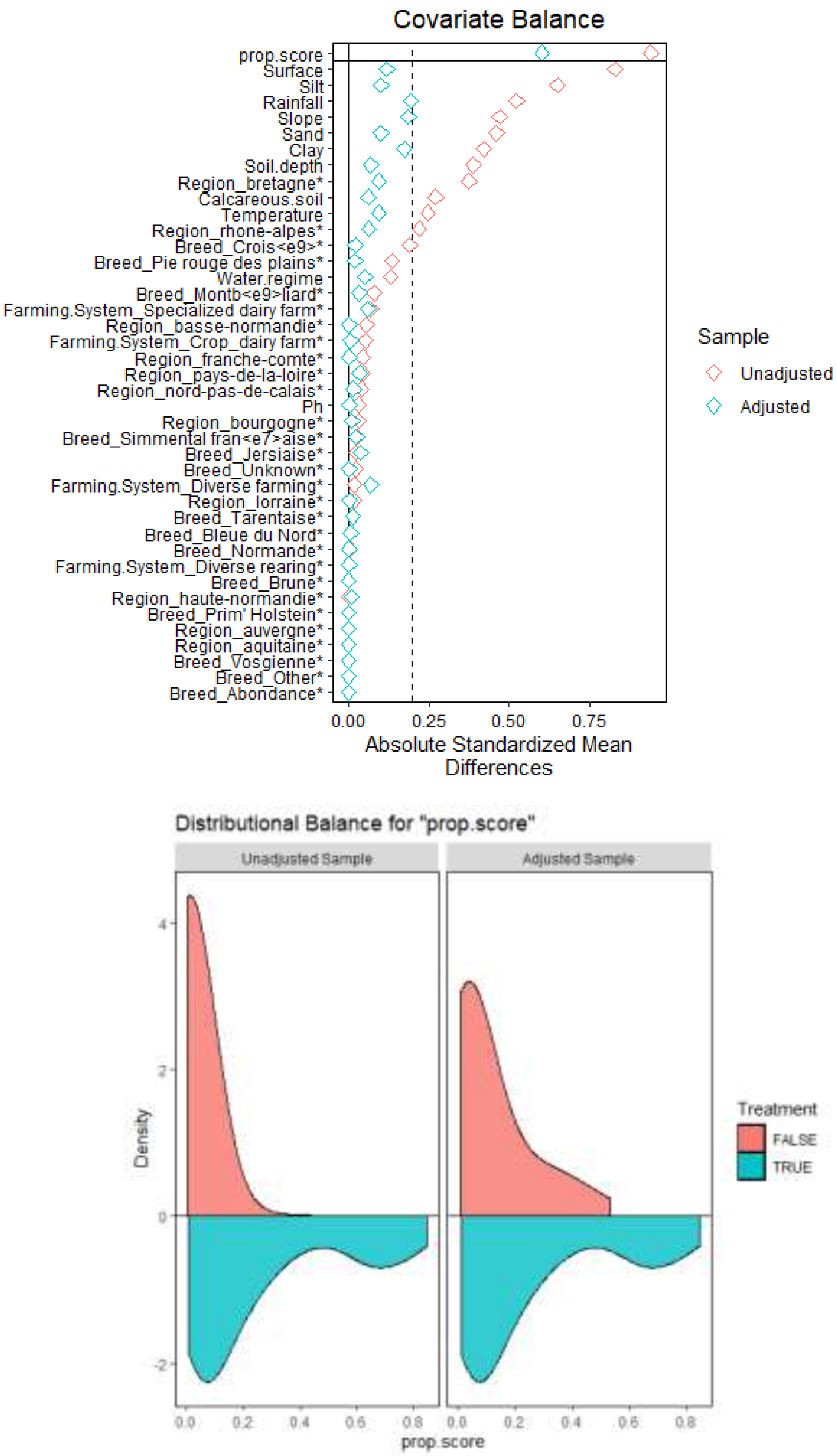
Variables	Description	Mean	St. Dev.	Min	Max
Gross margin per L	Gross margin per liter of FPCM milk, in €.	0.237	0.062	-0.354	0.627
Gross margin per LU	Gross margin per labor units in €.	75,698	37,650	-104,191	216,520
Gross margin per Ha	Gross margin per hectare in €.	1,783	707.3	-2,780	5,142
Gross GHGE	Gross GHGE per liter of FPCM milk, in kg CO2eq.	1.161	0.164	0.678	2.403
dLUC GHGE	Gross GHGE + dLUC GHGE per liter of FPCM milk, in kg CO2eq.	1.127	0.257	-1.915	2.205
dLUC + Practices GHGE	Gross GHGE + dLUC GHGE + impacts of practices on on-farm carbon sequestration per liter of FPCM milk, in kg CO2eq.	1.116	0.218	-1.102	2.059
iLUC GHGE	Gross GHGE + dLUC GHGE + iLUC GHGE per liter of FPCM milk, in kg CO2eq.	1.154	0.158	0.53	2.184
iLUC + Practices GHGE	Gross GHGE + dLUC GHGE + iLUC GHGE + impacts of practices on on-farm. carbon sequestration per liter of FPCM milk, in kg CO2eq.	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
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, dummy.				
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

	1 : Not wet* within 80 cm for over 3 months, nor wet within 40 cm for over 1 month				
	2 : Wet within 80 cm for 3 to 6 months, but not wet within 40 cm for over 1 month				
	3 : Wet within 80 cm for over 6 months, but not wet within 40 cm for over 11 months				
	4 : Wet within 40 cm depth for over 11 months				
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.				
Farming System	Type of farming specialization (dairy, dairy and crops, highly diversified)				

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

SI 6. Sensitivity analysis of the propensity score estimation

Figure SI 6. Covariate balance and common support check for organic and conventional farms' propensity score weighting



Before the propensity score weighting procedure, we can observe strong differences between organic and conventional farms in size, pedo-climatic conditions, location and breed, all of which are resorbed after the weighting procedure (Covariate balance graph in Figure SI 6). Thus, we can assess that the weighted organic and conventional farms have similar covariates, and that what explains the difference in outcomes between the farming systems is the treatment and not pedo-climatic variables (conditional independence assumption in SI 3). Similarly, after weighting the farms, the common support assumption is confirmed, as there is a sufficient overlap of the propensity score of organic and conventional farms (Distributional balance for *prop.score* (propensity score) graph in Figure SI 6). The sensibility analysis of the propensity score estimation (see SI 3and Table SI 6a) shows that the ATT estimates do not likely suffer from strong hidden bias as the correlation between the omitted variable and would need to be the probability of being treated would have to be higher than 0.29 for the ATT estimates (Gross GHGE here) to become insignificant.

Table SI 6a. Break-even correlation

Variable	Relative Influence	Correlation between a_i and the outcome	Break even correlation
Soil depth	23%	-0.138	0.678
Silt	15%	0.008	0.714
Surface	15%	0.041	0.286
Clay	9%	0.029	Does not exist
Slope	8%	-0.003	0.766
Sand	7%	-0.092	Does not exist
Rainfall	5%	-0.150	0.693
Herd Size	4%	-0.170	Does not exist
Region	4%	0.169	Does not exist
Calcareous soil	4%	-0.110	Does not exist
Ph	2%	0.090	0.719
Water regime	2%	0.018	Does not exist
Breed	2%	-0.041	Does not exist
Farming System	1%	0.013	Does not exist
Temperature	0%	-0.162	Does not exist

Table SI 6b. Propensity score weighting and bias-adjusted ATT estimation

	Gross GHGE	dLUC GHGE	dLUC + Seq. Practices GHGE	dLUC + iLUC + Seq. Practices GHGE	iLUC GHGE 2.5%	iLUC GHGE 97.5%	Gross margin	Gross margin	Gross margin
	kgCO2e.L^{-1}	kgCO2e.L^{-1}	kgCO2e.L^{-1}	kgCO2e.L^{-1}	kgCO2e.L^{-1}	kgCO2e.L^{-1}	€.L^{-1}	€.Ha^{-1}	€.LU^{-1}
Treatment - Organic	0.01	-0.07	-0.20***	-0.13***	-0.21***	-0.12***	0.17***	273.57***	11,853.57***
	(0.03)	(0.06)	(0.05)	(0.03)	(0.05)	(0.04)	(0.01)	(60.51)	(3,583.55)
Slope	0.002	-0.02**	-0.01**	0.002	-0.01***	0.01	-0.0004	-14.73**	-1,098.32***
	(0.003)	(0.01)	(0.005)	(0.003)	(0.01)	(0.004)	(0.001)	(5.83)	(342.34)
Rainfall	-0.0002**	0.0002	0.0001	-0.0002**	0.0002	-0.0003**	-0.0000	-0.05	-13.05
	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0000)	(0.21)	(10.89)
Temperature	-0.04**	0.15***	0.06***	-0.08***	0.09***	-0.12***	0.01**	76.10**	4,658.56**
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.01)	(37.93)	(1,924.30)
Soil.depth	-0.0000	0.001	0.001	0.0000	0.001	-0.0001	-0.0002	-0.89	-111.40
	(0.001)	(0.001)	(0.0005)	(0.001)	(0.001)	(0.001)	(0.0002)	(1.15)	(71.91)
Water.regime	-0.05	-0.14	-0.10	-0.03	-0.12	-0.01	0.03	-2.22	9,841.41
	(0.08)	(0.16)	(0.10)	(0.09)	(0.13)	(0.11)	(0.03)	(173.50)	(10,216.72)
Calcareous.soil	-0.01	-0.17	-0.05	0.07	-0.08	0.11	0.04	-66.54	-8,415.72
	(0.10)	(0.21)	(0.15)	(0.12)	(0.18)	(0.15)	(0.05)	(270.15)	(13,487.27)
Ph	0.04	-0.12	-0.09	0.03	-0.12	0.07	-0.01	-59.93	-1,774.32
	(0.04)	(0.10)	(0.07)	(0.05)	(0.08)	(0.06)	(0.02)	(107.57)	(4,962.97)
Clay	0.0004	0.02**	0.01*	-0.003	0.01**	-0.01	0.001	-6.04	-106.88
	(0.004)	(0.01)	(0.01)	(0.004)	(0.01)	(0.01)	(0.002)	(9.62)	(447.43)
Silt	-0.01**	0.0001	0.001	-0.004	0.002	-0.01	0.002	15.46***	640.01**
	(0.003)	(0.01)	(0.004)	(0.003)	(0.005)	(0.004)	(0.001)	(5.49)	(280.41)
Sand	-0.003*	0.004	0.002	-0.004	0.004	-0.01*	0.0001	2.35	194.60
	(0.002)	(0.005)	(0.003)	(0.002)	(0.004)	(0.003)	(0.001)	(4.84)	(201.98)
Specialized dairy farm	0.07*	-0.22**	-0.16**	0.07	-0.20***	0.13**	-0.01	-127.51	-11,967.34**
	(0.04)	(0.10)	(0.06)	(0.05)	(0.08)	(0.06)	(0.01)	(78.30)	(5,949.39)
Crop and Dairy farm	-0.08	-0.22*	-0.22*	-0.11	-0.24*	-0.08	-0.02	-177.25	-13,264.95
	(0.06)	(0.12)	(0.12)	(0.09)	(0.13)	(0.11)	(0.02)	(124.72)	(10,306.10)
Diverse farming	0.03	-0.24***	-0.19***	0.02	-0.24***	0.07	-0.02	-140.47	-13,239.96*
	(0.05)	(0.09)	(0.07)	(0.06)	(0.08)	(0.07)	(0.03)	(112.46)	(7,462.56)
Breed_Abondance	-0.04	-0.19	-0.04	0.08	-0.07	0.11	-0.07*	27.44	-27,817.72**
	(0.09)	(0.17)	(0.11)	(0.10)	(0.13)	(0.12)	(0.04)	(237.39)	(12,974.83)
Breed_Other	0.19*	-0.15	0.05	0.31***	-0.01	0.38***	-0.12***	-547.70**	-47,605.78***
	(0.10)	(0.23)	(0.16)	(0.10)	(0.19)	(0.12)	(0.04)	(225.25)	(12,168.22)
Breed_Bleue du Nord	-0.08	-0.33	-0.19	0.01	-0.23	0.06	-0.02	122.89	-16,068.23
	(0.10)	(0.20)	(0.13)	(0.14)	(0.15)	(0.17)	(0.04)	(217.89)	(10,672.69)
Breed_Brune	-0.19**	-0.31*	-0.13	-0.03	-0.15	-0.005	-0.03	305.43	-4,689.53
	(0.09)	(0.19)	(0.14)	(0.09)	(0.16)	(0.11)	(0.04)	(228.26)	(11,960.05)
Breed_Croisé	-0.06	-0.30*	-0.09	0.09	-0.13	0.14	-0.07**	39.79	-28,555.07***
	(0.08)	(0.15)	(0.10)	(0.08)	(0.12)	(0.10)	(0.03)	(196.09)	(9,961.37)
Breed_Jersiaise	-0.08	-0.33*	-0.10	0.09	-0.14	0.14	-0.06	150.72	-18,422.16
	(0.09)	(0.17)	(0.11)	(0.09)	(0.13)	(0.11)	(0.04)	(273.38)	(14,540.54)

Breed_Montbéliard	0.29***	0.09	0.35***	0.50***	0.31**	0.55***	-0.09**	-434.16*	-52,477.75***
	(0.10)	(0.18)	(0.12)	(0.10)	(0.14)	(0.12)	(0.04)	(234.58)	(12,067.69)
Breed_Normande	-0.04	-0.24	-0.07	0.09	-0.10	0.13	-0.06*	-8.17	-28,479.70***
	(0.08)	(0.15)	(0.10)	(0.08)	(0.12)	(0.10)	(0.03)	(190.22)	(9,660.42)
Breed_Pie rouge des plains	-0.10	-0.15	0.18	0.22*	0.18	0.23	-0.04	56.03	-9,508.74
	(0.15)	(0.18)	(0.14)	(0.13)	(0.17)	(0.16)	(0.04)	(266.60)	(22,183.79)
Breed_Prim' Holstein	0.24	-0.20	0.03	0.37	-0.04	0.46	-0.12	-213.20	-34,177.55**
	(0.41)	(0.20)	(0.21)	(0.49)	(0.18)	(0.58)	(0.08)	(280.58)	(16,248.82)
Breed_Simmental française	-0.38***	0.24	0.01	-0.47**	0.11	-0.60**	0.04	467.66*	1,212.82
	(0.15)	(0.20)	(0.12)	(0.19)	(0.15)	(0.24)	(0.04)	(273.99)	(15,339.27)
Breed_Tarentaise	0.08	-0.54**	-0.30*	0.18	-0.40**	0.31	-0.08	-315.34	-27,768.38*
	(0.14)	(0.25)	(0.16)	(0.19)	(0.19)	(0.23)	(0.06)	(254.02)	(14,374.42)
Breed_Vosgienne	-0.17	-0.32	-0.42***	-0.30**	-0.44**	-0.27*	-0.02	302.33	-39,514.31**
	(0.12)	(0.22)	(0.16)	(0.13)	(0.18)	(0.16)	(0.05)	(305.00)	(15,877.06)
Region_Auvergne	-0.04	0.04	0.05	-0.01	0.06	-0.03	0.06***	558.48*	15,659.30
	(0.07)	(0.10)	(0.08)	(0.07)	(0.09)	(0.09)	(0.02)	(298.56)	(32,079.47)
Region_Basse-Normandie	0.25***	-0.32*	-0.16	0.28***	-0.25*	0.40***	-0.02	-552.33***	-51,453.56***
	(0.08)	(0.18)	(0.12)	(0.09)	(0.15)	(0.12)	(0.02)	(183.32)	(9,275.87)
Region_Bourgogne	0.23**	-0.07	0.16*	0.39***	0.11	0.46***	-0.05**	-393.83***	-64,047.37***
	(0.09)	(0.15)	(0.09)	(0.13)	(0.11)	(0.16)	(0.03)	(135.70)	(7,461.63)
Region_Bretagne	0.21***	0.02	0.02	0.16**	-0.01	0.20**	0.001	-286.74**	-36,645.13***
	(0.07)	(0.12)	(0.09)	(0.08)	(0.10)	(0.09)	(0.02)	(143.34)	(7,181.95)
Region_Franche-Comté	0.20*	-0.20	-0.01	0.29*	-0.08	0.37*	0.01	-335.74**	-33,271.94***
	(0.10)	(0.19)	(0.11)	(0.16)	(0.13)	(0.20)	(0.04)	(160.11)	(11,278.32)
Region_Haute-Normandie	0.18*	-0.10	-0.13	0.09	-0.18	0.15	0.06*	105.03	-26,798.40**
	(0.10)	(0.19)	(0.15)	(0.11)	(0.17)	(0.13)	(0.03)	(206.10)	(10,897.82)
Region_Lorraine	0.21***	0.08	0.20*	0.30***	0.19	0.33***	0.01	-278.06*	-19,426.82*
	(0.07)	(0.16)	(0.11)	(0.09)	(0.13)	(0.11)	(0.03)	(153.97)	(10,862.93)
Region_Nord-Pas-de-Calais	0.23***	-0.03	0.07	0.27***	0.03	0.32***	-0.08***	-450.75***	-47,946.33***
	(0.04)	(0.15)	(0.09)	(0.05)	(0.11)	(0.08)	(0.03)	(131.67)	(4,856.05)
Region_Pays-de-la-Loire	0.30***	-0.03	0.06	0.32***	0.01	0.39***	-0.04	-410.20**	-53,189.36***
	(0.09)	(0.12)	(0.09)	(0.10)	(0.10)	(0.12)	(0.03)	(189.76)	(7,535.73)
Region_Rhône-Alpes	0.27***	-0.21	-0.01	0.36**	-0.09	0.46**	-0.04	-413.96***	-49,430.22***
	(0.10)	(0.14)	(0.08)	(0.15)	(0.10)	(0.19)	(0.03)	(140.35)	(9,581.19)
Herd.Size	-0.001	0.01***	0.004***	-0.0004	0.01***	-0.002***	0.0005***	11.60***	421.63***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.0002)	(1.29)	(67.57)
Surface	0.001*	-0.01***	-0.004***	0.001	-0.01***	0.002***	-0.0001	-11.87***	-202.94***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.0002)	(1.37)	(64.80)
Constant	1.75***	-0.03	0.72*	2.09***	0.44	2.45***	0.11	988.78	75,013.07**
	(0.31)	(0.53)	(0.43)	(0.32)	(0.50)	(0.39)	(0.13)	(732.95)	(32,352.84)

Note: * p<0.1; ** p<0.05; *** p<0.01

Due to the presence of dummy variables, the treatment effect 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.

SI 7. ATT estimation

Table SI 7a. Propensity score weighting and ATT.

	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	Gross Margin	Gross Margin	Gross Margin without price premium	Total Revenue	Value Added
	$kgCO2e.L^{-1}$	$kgCO2e.L^{-1}$	$kgCO2e.L^{-1}$	$kgCO2e.L^{-1}$	$kgCO2e.L^{-1}$	$kgCO2e.L^{-1}$	$€.L^{-1}$	$€.Ha^{-1}$	$€.LU^{-1}$	$€.LU^{-1}$	$€.LU^{-1}$	$€.LU^{-1}$
	(1)	(2)	(3)	(5)	(6)	(7)	(8)	(9)	(10)	(12)	(11)	(13)
Treatment Effet - Organic	0.03 (0.03)	-0.20** (0.09)	-0.28*** (0.06)	-0.10** (0.04)	-0.31*** (0.08)	-0.06 (0.06)	0.11*** (0.01)	-117.2 (88.57)	-5,114.1 (4,524)	-19,937*** (3,869)	-32,344*** (5,471)	-5,717 (3,907)
Constant	1.21*** (0.01)	0.92*** (0.06)	0.97*** (0.04)	1.19*** (0.01)	0.92*** (0.05)	1.25*** (0.03)	0.22*** (0.005)	1,378.6*** (40.95)	66,398*** (1,833)	66,398*** (1,833)	125,996*** (2,713)	87,639*** (1,882)
Robustness – without farms' surface	0.04 (0.03)	-0.23*** (0.09)	-0.31*** (0.06)	-0.10** (0.04)	-0.35*** (0.07)	-0.05 (0.05)	0.11*** (0.01)	-179.12** (87.37)	-4,435.1 (4,459)	-19,719*** (3,793)	-31,648*** (5,325)	-5,044 (4,506)
Robustness – without herds' size	0.03 (0.03)	-0.22*** (0.08)	-0.30*** (0.05)	-0.10** (0.04)	-0.34*** (0.07)	-0.05 (0.05)	0.11*** (0.01)	-122.5 (86.78)	-6,052.1 (4,529.)	-20,875*** (3,876)	-34,029*** (5,422)	-6,657 (4,578)
Robustness – t-tests	0.08** (0.03)	-0.41*** (0.07)	-0.44*** (0.04)	-0.06 (0.04)	-0.51*** (0.05)	0.04 (0.05)	0.09*** (0.01)	-534.7*** (80.1)	-14,762*** (4,200)	-29,584*** (3,399)	-43,666*** (4,866)	16,223*** (4,257)

Note: * p<0.1; ** p<0.05; *** p<0.01

The constant corresponds to the weighted average of counterfactual conventional farms. The ATT reported in the manuscript, expressed in percentage points this weighted average and correspond to the Treatment Effect to Constant ratio. 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.

Table SI 7b. Propensity score weighting and ATT without excluding farms misreporting labor use.

	Gross GHGE	dLUC GHGE	dLUC + Seq. Practices GHGE	iLUC + dLUC Seq. Practices GHGE	dLUC + iLUC + Seq. Practices 2.5%	dLUC + iLUC + Seq. Practices 97.5%	Gross Margin	Gross Margin	Gross Margin	Gross Margin without price premium	Total Revenue	Value Added
	$kgCO2e.L^{-1}$	$kgCO2e.L^{-1}$	$kgCO2e.L^{-1}$	$kgCO2e.L^{-1}$	$kgCO2e.L^{-1}$	$kgCO2e.L^{-1}$	$€.L^{-1}$	$€.Ha^{-1}$	$€.LU^{-1}$	$€.LU^{-1}$	$€.LU^{-1}$	$€.LU^{-1}$
Treatment Effet - Organic	0.03 (0.03)	-0.19^{**} (0.09)	-0.28^{***} (0.06)	-0.10^{**} (0.04)	-0.31^{***} (0.08)	-0.06 (0.06)	0.15^{***} (0.01)	38.2 (96.1)	-2,016 (5,059)	$-9{,}195^{**}$ (4,745)	$-38{,}636^{***}$ (5,802)	$-9{,}817^{***}$ (4,801)
Constant	1.21^{***}	0.92^{***}	0.97^{***}	1.19^{***}	0.97^{***}	1.31^{***}	0.23^{***}	1041^{***}	$71{,}765^{***}$	$71{,}765^{***}$	$133{,}574^{***}$	$93{,}026^{***}$
	(0.01)	(0.06)	(0.05)	(0.01)	(0.05)	(0.03)	(0.005)	(42.2)	(2,215)	(2,215)	(3,236)	(2,268)

Note: * p<0.1; ** p<0.05; *** p<0.01

The constant corresponds to the weighted average of counterfactual conventional farms. The ATT reported in the manuscript, expressed in percentage points this weighted average and correspond to the Treatment Effect to Constant ratio. dLUC GHGE is 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.

Table SI 7c. Propensity score weighting and ATT with a 50 years' horizon for carbon sequestration and emission

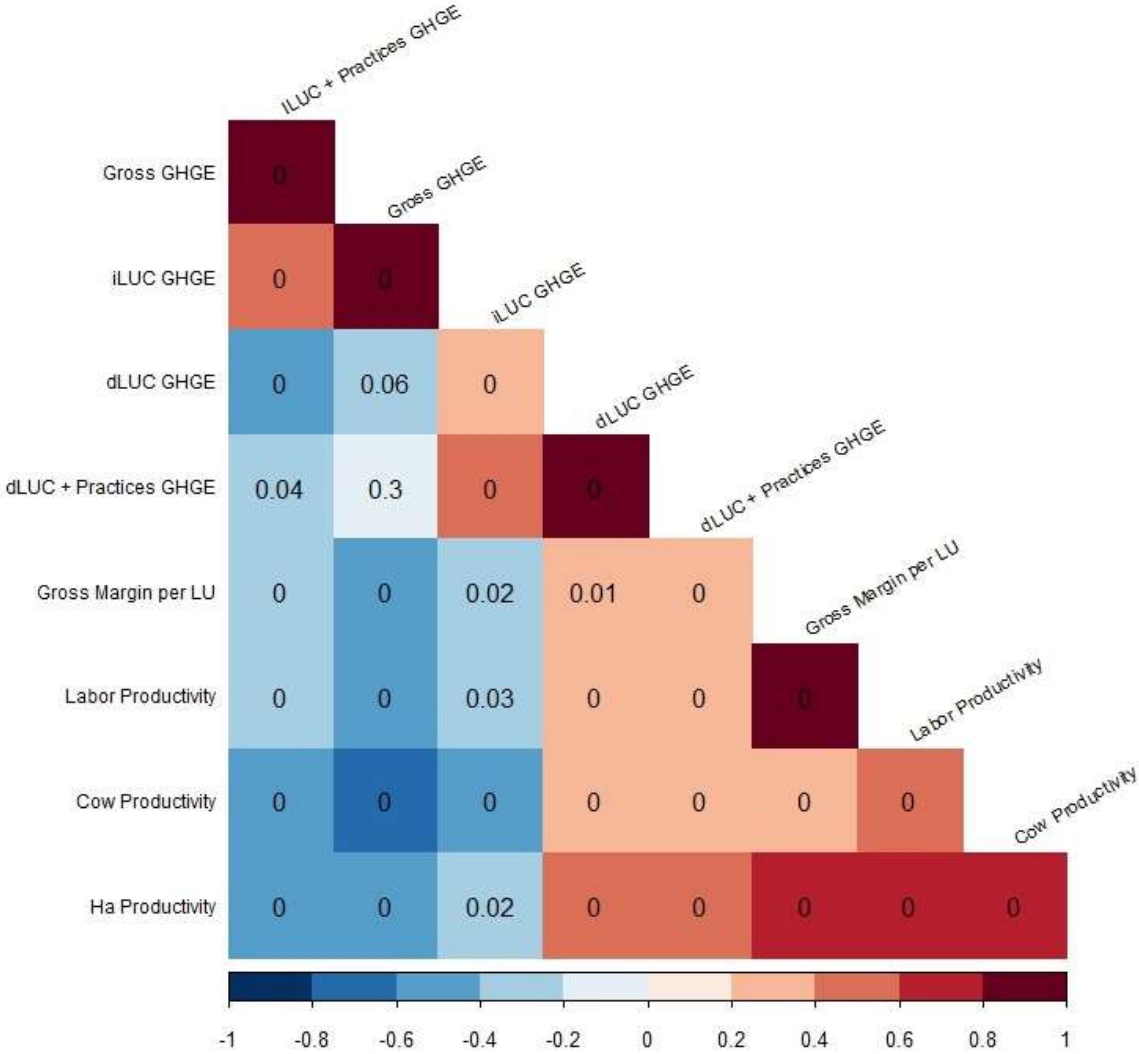
	Gross GHGE	dLUC GHGE	dLUC + Seq. Practices GHGE	dLUC +iLUC + Seq. Practices GHGE	dLUC +iLUC + Seq. Practices 2.5%	dLUC +iLUC + Seq. Practices 97.5%
	$kgCO2e.L^{-1}$	$kgCO2e.L^{-1}$	$kgCO2e.L^{-1}$	$kgCO2e.L^{-1}$	$kgCO2e.L^{-1}$	$kgCO2e.L^{-1}$
Treatment Effet - Organic	0.03 (0.03)	-0.06 (0.04)	-0.09^{***} (0.03)	-0.03 (0.03)	-0.10^{*} (0.03)	0.01 (0.05)
Constant	1.21^{***}	1.09^{***}	1.12^{***}	1.19^{***}	1.10^{***}	1.21^{***}
	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.01)

Note: * p<0.1; ** p<0.05; *** p<0.01

The constant corresponds to the weighted average of counterfactual conventional farms. The ATT reported in the manuscript, expressed in percentage points this weighted average and correspond to the Treatment Effect to Constant ratio. dLUC GHGE is 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.

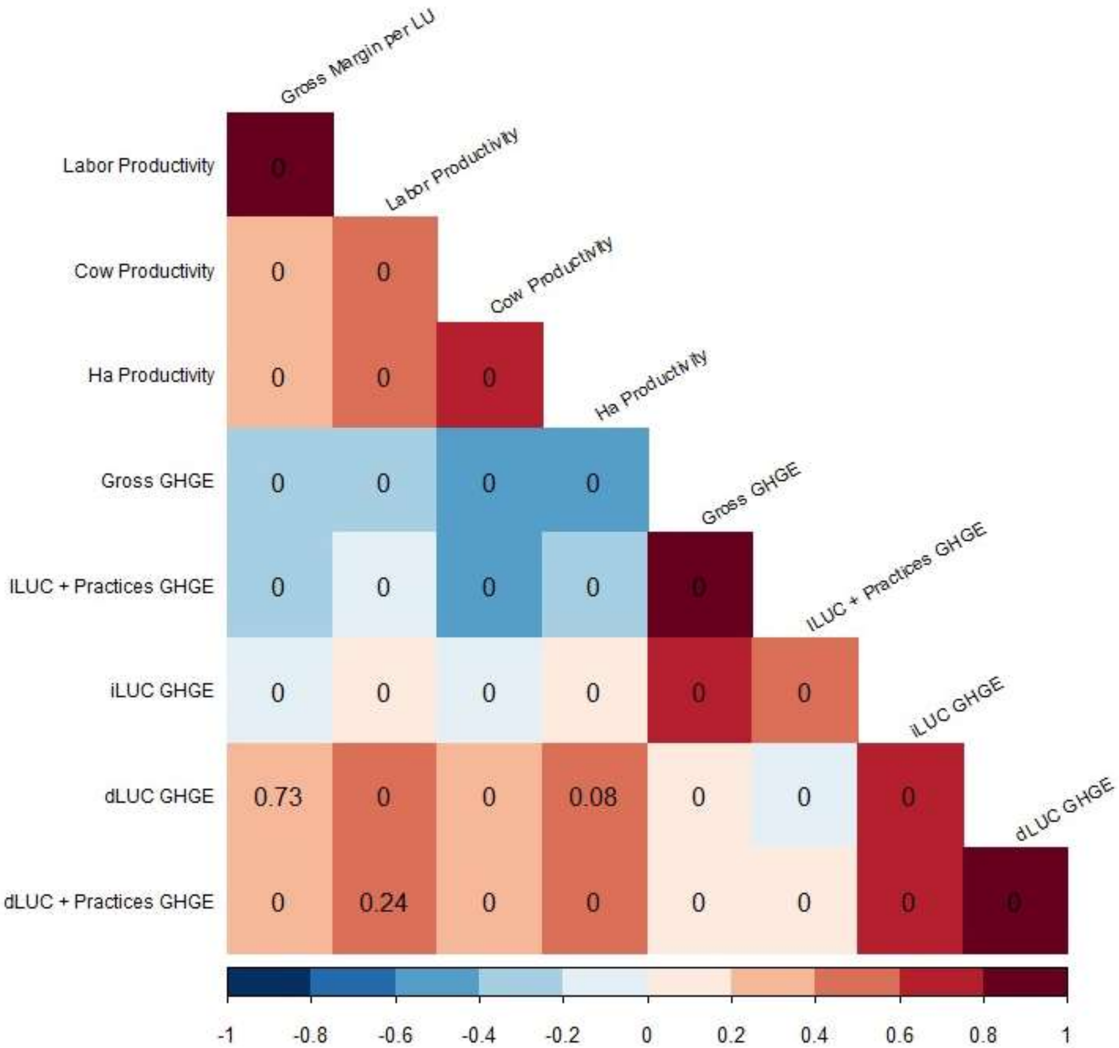
SI 8. Correlation plots of key farms' indicators

Figure SI 8a. Correlation plot for the performances' indicators of organic farms



The numbers in each cells represent the p.value of the correlation. The strength and direction of the correlation is given by the colour of the cells.

Figure SI 8b. Correlation plot for the performances' indicators conventional farms



The numbers in each cells represent the p.value of the correlation. The strength and direction of the correlation is given by the colour of the cells.

Chapter 3

Once a quality-food consumer, always a quality-food consumer? Consumption patterns of organic, label rouge and geographical indications in French scanner data

Note: This chapter is based on a published paper under the same title, coauthored with Stéphane De Cara and Valentin Bellassen.

3.0. Abstract

The aim of this study is to analyze the behavior of French consumers with respect to food products under various quality labels (organic, *label rouge*, and geographical indications). In particular, we investigate if consumers who once purchase a product under a given label tend to purchase a large fraction of this product (and other products) under the same label.

Using a large scanner database, the regularity of quality-food consumption is analyzed through the relative frequency of conventional and quality purchases. The respective roles in regular consumption of product attributes, availability and household characteristics are then examined using a random utility model.

Regular organic consumers purchase around 28% of the organic market value, with variations depending on products. We find that product attributes are more related to regular organic behavior than household characteristics. In particular, product availability and product family (vegetables, eggs, milk, etc.) play a key role whereas low-price organic products are not associated with more regular consumption.

Acknowledging the existence of regularity in organic consumption and understanding its variation between product categories should lead public policies to more often target specific products in order to develop quality-food consumption.

Keywords: *quality food, consumption behavior, organic, regularity, Lancaster.*

3.1. Introduction

Over the last few years, the consumption of organic food has experienced a rapid and steady growth. In France, its value rose from € 5.9 billion in 2015 to € 9.7 billion—i.e., 5% of food expenditures—in 2018 (Agence Bio, 2019a). In a recent French survey, about one in eight respondents declares eating at least one organic product a day (Agence Bio, 2019b). Other quality labels—such as Protected Designation of Origin (PDO), Protected Geographical Indication (PGI) or *label rouge*—also represent a substantial and increasing share in food consumption. For some products, these labels dominate organic ones as a quality sign. This is notably the case for cheese, for which geographical indications represent 11% of the French market, a much higher share than that of organic cheese (2%).

The rising demand for quality-food products—defined here as products certified as organic, PDO, PGI or *label rouge*—impacts farming practices, land use, and value chains. As an illustration, the area devoted to organic agriculture in France has increased by 48.3% from 2015 to 2018, reaching 7.5% of the total agricultural area. As for other quality signs, between 2015 and 2019, the volume of meat and dairy products, fish, and eggs produced under these labels has increased from 602 to 665 thousand tons, reaching 1.5% to 1.8% of market share in these categories (INAO, 2019).

Providing consumers with healthier and higher-quality food while leveraging the potential health and environmental benefits from less intensive agricultural practices without affecting too negatively farmers' income has attracted renewed interest from policy makers. The development of the production and consumption of quality-food products (organic food, but also other quality signs) has become a central objective in agricultural and food policies. EGalim, a French law on food and agriculture passed in 2018, provides a good illustration of this trend in public policies.

An adequate understanding of the demand-side determinants of quality-food consumption is thus critical to assess the potential impacts of such policies. In particular, it is important to determine whether the demand for these products comes primarily from a large base of occasional consumers or a small base of '*regular'* ones. The recent increase in quality-food consumption is consistent with both a larger consumer base and an increasing share of quality-food in individual purchases. Which explanation dominates remains however an open question. This raises further questions regarding consumers' behavior with respect to quality-food products. Do consumers tend to routinely and systematically purchase a product under the same label? If so, is this behavior restricted to some products, or consistent across the food basket? The answers to these questions may have strong implications for the design and targeting of the policies aiming to develop quality-food consumption.

In this article, we define a '*regular'* consumer—as opposed to an '*occasional'* one—as a consumer who predominantly buys a given product with a consistent quality. Regularity in quality-food consumption is thus related to how consumers perceive and value quality labels. In this regard, previous research has shown that credence attributes—i.e., attributes that the consumer cannot identify through search nor experience—play a major role in the decision to buy quality-food products (Massey et al., 2018; Rana and Paul, 2017). If the demand for quality-food products is primarily driven by credence attributes, one may expect that regularity should be the rule rather than the exception.

Yet, this intuition is at odds with recent evidence. In a study of organic food purchasing behaviors in France, Boizot-Szantai et al., (2017) find that organic food represents only 8.1% of total food expenditures of the consumers whose organic budget share is above the top quintile. This suggests that, even for the consumers who value organic food the most, a large share of their purchases goes to non-organic products. That is not to say, however, that regularity is necessarily absent from consumers' behavior. A consumer may well always choose to buy the organic version of some products, and systematically prefer the conventional version (or another quality label) of other products. The aggregation of all food expenditures at the food-basket level therefore may thus mask regularity patterns that occur at the product level.

Our main objective is to identify and document regularity patterns in food purchasing behaviors at various levels of aggregation and for various quality labels, and to study the interplay with other drivers of quality-food consumption such as price, availability and socio-demographic characteristics of quality-food consumers.

Our study thus contributes to the large body of literature—in economics, but also in sociology and marketing science—that has examined consumers' behavior and attitude towards quality-food products. The vast majority of this literature is focused on organic consumption, which covers a wider range of food products than other quality signs. This literature has investigated the effects of price, income, and socio-demographic variables on organic food consumption, as well as the role of the relative preferences for products objective characteristics (taste, color, etc.) and considerations regarding health, the environment, ethics, or animal welfare.

Quantitative studies in this literature are based on two broad types of approaches. First, a number of studies use surveys or controlled experiments. These studies rely on stated preferences to elicit consumers' preferences or willingness to pay for various goods with different characteristics or attributes. The experimental design makes it possible to disentangle potential confounding factors. However, they often rely on small sample sizes and/or may be subject to sampling biases. Furthermore, stated intentions to buy quality food may overestimate actual purchases (Sun and Morwitz, 2010). Studies in the second category are based on observational data. Those relying on scanner data are particularly relevant for the present study. By using detailed records of actual and repeated purchases by a large and representative sample of consumers, such studies allow to overcome some of the limitations faced by survey-based and experimental approaches. Observed purchases do not, however, directly inform on consumers' preferences. In addition, such data mostly pertain to purchases for food-at-home consumption at the household level, which may differ from actual consumption at the individual level.

This literature has shed interesting light on the socio-demographic profile of quality-food consumers, as well as on the influence of product attributes on consumption behavior. For example, findings suggest that organic food consumers tend to be more educated and have higher income than conventional food consumers. They are more likely to be female and to have children, especially newborns (Gracia and de Magistris, 2008; Hughner et al., 2007). They also spend more on food and have a healthier diet (Boizot-Szantai et al., 2017). Several studies underline the key importance of credence attributes in attitudes toward organic food. Consumers tend to place more value on credence attributes of organic products than on their search and experience attributes (Massey et al., 2018; Rana and Paul, 2017). The influence of credence attributes on the probability of purchasing organic products has been found to be larger than that of education, marital status, and income (Padilla Bravo et al., 2013). The review by Rödiger and Hamm (2015) shows inconclusive evidence with respect to the effect of price on organic consumption. Results from observational studies indicate that the effect of economic determinants of organic consumption, most notably price and availability, varies across products and types of retail stores (Buder et al., 2014; Dimitri and Dettmann, 2012; Padel and Foster, 2005).

Regularity in organic food consumption has been much less studied than the influence of the socio-demographics variables, price, income, or product attributes. Some survey-based studies have examined the factors influencing the probability that a consumer defines himself or herself as a regular organic consumer (Barrena and Sánchez, 2010; Baudry et al., 2019; Kesse-Guyot et al., 2013; Oates et al., 2012; Onyango et al., 2007; Pearson et al., 2013; Treu et al., 2017). However, as these studies are based on stated consumption averaged at the whole food basket level, it is difficult to draw robust conclusions on actual purchases at finer aggregation levels. Observational studies based on scanner data (Boizot-Szantai et al., 2017; Lacour et al., 2018a) provide some interesting findings about purchasing patterns, but, the focus in these studies is on the share of organic food in total food expenditures. Considering all food products together may mask regularity patterns at a more disaggregated level.

Although expectedly important, the availability of quality-food products has also received less attention than other potential determinants (Dimitri and Dettmann, 2012). One reason lies in the difficulty to accurately quantify availability. As a consequence, availability has been overlooked in most survey-based and observational studies of organic consumption.

In this paper, we use a large scanner dataset of food purchases in France, provided by Kantar®, which provides detailed records (quantities, price, type of retail store, etc.) of purchases of 237 food products by an unbalanced panel of 12,453 French households between 2011 and 2016, along with socio-demographic information about households (age, income, *département* of residence, household size, etc.). This dataset enables to decompose household food purchases at a fine level of disaggregation in terms of products. Importantly, it informs about the labels (organic, PDO, PGI, *label rouge*), if any, attached to each purchased product.

In order to identify regularity, we use two complementary approaches. For a given product or category of products, we first examine whether the distribution of purchases under a given label is compatible with a large base of occasional consumers, or a small base of quality regulars. In a second step, we then investigate the influence of various determinants of the probability that a consumer is regular for a given product and label. The variables accounted for in this analysis include various characteristics of products (price, retailer brand, and availability), retail stores, and households (socio-demographic variables, income, city size, etc.).

We take advantage of the richness of this information to address four main questions. First, can the consumption of a given (set of) product(s) be characterized as 'regular'? In other words, do consumers purchase mostly one version of the product (conventional, organic, PDO, PGI, or *label rouge*) or do they buy a mix of various versions? Second, is regularity consistent across the food basket? Put differently, are quality regulars for a given product also regular for most of all other products they purchase? Third, how much of the total demand for quality-food products comes from regular consumers? Fourth, how do product attributes and household characteristics interplay in the probability that a given household is a quality regular for a given food product?

Our contribution is threefold. First, we address these questions for a wide range of products sold under various labels. Contrary to most of the literature, which is predominantly focused on organic products, we extend the scope of the analysis to other quality labels such as PDO, PGI, or *label rouge.* Products under these labels have several important features in common with organic products. In particular, their production is often based on extensive farming practices with a potential to improve the sustainability of food systems (Arfini and Bellassen, 2020) and credence attributes play a major role in consumers' decision to buy these products. They do however differ from organic products in a number of dimensions, such as the range of products covered by the label, availability, price, perception of environmental and health benefits, organoleptic characteristics, aspect, etc. We investigate whether different labels can be associated with different purchasing behaviors in terms of regularity. Besides, previous studies were often focused on only one or a few products. The large number of products (237) examined in this article allows us to further study how consumers' behaviors varies with the type of products (Buder et al., 2014; Chekima et al., 2017; Padel and Foster, 2005).

Second, we identify regularity patterns in quality-food consumption, but not for all products nor all labels. Such findings would not have been possible with the level of aggregation and coverage used in previous studies (Boizot-Szantai et al., 2017; Lacour et al., 2018a).

Third, we propose a new indicator of availability of quality-food products. The main difficulty is that, availability of products that are not bought by consumers in the sample cannot be directly observed. We circumvent this difficulty by constructing a novel indicator based on web-scrapping techniques applied to online catalogues of retail stores. This indicator allows us to determine the share of retail stores where any given product can be found within a given region in the total number of stores visited by a given consumer. This indicator is found to be strongly and positively correlated to the probability that a consumer is an organic regular.

In sum, after detailing our methodology, we present the results organized in two axis, the first one on the identification of quality-food regular consumption and the second on its determinants, then discuss them and conclude.

3.2. Methodology

3.2.1. Theoretical framework

Consumers often have the choice between several versions of the same food product, e.g. between conventional, organic, PDO, PGI, or *label rouge*. Although different versions of the same product share some common characteristics, they may also differ along various attributes. Some of these attributes are specific to the product itself, whereas others are attached to the perceptions of the label by the consumers. Some can be observable through search and experience. Others remain unobservable and are therefore akin to credence attributes.

Previous research has shown that credence attributes are major drivers of organic and other quality-food purchases (Barrena and Sánchez, 2010; Gracia and de Magistris, 2008; Massey et al., 2018; Rana and Paul, 2017). Most of the attributes that define a product—regardless of the presence of a label—can be identified by search and/or experience. In contrast, most of the distinctive attributes of quality-food items are credence attributes. Note that some of the credence attributes associated with a given label may be shared by all products under the same label. It is thus important to disentangle consumers' preferences towards (i) food products regardless of their quality label and (ii) credence attributes associated with quality labels (or absence thereof) across all products. Note also that preferences for a quality label may vary from one product to the other.

It is useful to illustrate the consumer problem by a simple theoretical framework inspired by Lancaster's approach to consumer demand (Lancaster, 1966) and akin to the individual utility model of the BLP model (Berry et al., 1995). This simple model accounts for search and experience as well as credence attributes. Consider the choice faced by consumer i over a set J of food products (indexed by j). Food products are available in various qualities indexed by l in L, including a conventional version (indexed by $l = c$) and different quality labels. Assume that the consumer preferences can be represented by a utility function $U_i\left(q_{i0};\ \{u_{ijl}(q_{ijl})\}_{j\in J,l\in L}\right)$, where q_{i0} is the quantity of a composite non-food item, q_{ijl} is the quantity of j-th product of quality l, and $u_{ijl}(.)$ is the respective subutility function. For simplicity, assume that $u_{ijl}(q_{ijl})$ takes the following simple Cobb-Douglas form:

$$u_{ijl}(q_{ijl}) = a_{ijl}\ln(\mathrm{q}_{ijl}) = a_{ij}^{se}\ln(\mathrm{q}_{ijl}) + a_{il}^{cr}\ln(\mathrm{q}_{ijl}) + a_{ijl}^{se\times cr}\ln(\mathrm{q}_{ijl}) \tag{1}$$

The formulation in Eq. (1) characterizes the consumer utility with respect to product j of quality l. It is parameterized by $a_{ijl} > 0$, which can be decomposed into three terms capturing the utility derived from search and experience attributes (se), credence attributes (cr), and an interaction term ($se \times cr$). The parameter a_{ij}^{se} parametrizes the utility for the j-th product regardless of its quality. It captures how much the consumer values product-specific attributes that can be apprehended by search and experience (e.g., in the case of an apple, characteristics such as the fact that it is a rather small, round, acid and sweet fruit). a_{il}^{cr} parameterizes the utility for quality *l* across all products. This parameter is thus label-specific and captures how consumer *i* values the credence attributes attached to label *l* (e.g., in the case of organic products, the implications that farming practices do not rely on pesticides nor synthetic fertilizers). The third term $a_{ijl}^{se\times cr}$ captures the interaction between the search and experience attributes of product *j* with the credence attributes associated with quality *l*. This reflects that the credence attributes attached to a specific label may vary from one product to the other (e.g., the consumer may value more organically-produced apples than organically-produced eggs). Further assume that the price of the conventional version of the product ($l = c$) is lower than the price of all other quality versions of the product. For simplicity, we normalize the parameters in Eq. (1) so that $a_{ic}^{cr} = a_{ijc}^{se\times cr} = 0$ for all *j*.

The quantities q_{ijl} that maximize the consumer utility subject to the budget constraint depend on prices and income, as well as on the elasticities of substitution between products and qualities implied by the form of $U_i(.)$. One expects that the demand in product *j* of quality $l \neq c$ to be close to 0 if a_{il}^{cr} and $a_{ijl}^{se\times cr}$ are both close to 0—i.e., if the credence attributes attached to the label l are perceived as unimportant by the consumer relative to the search and experience attributes of the product. If this condition holds for all $l \neq c$, the product is predominantly purchased in its conventional version and the consumer is said to be a conventional regular. Conversely, if $a_{il}^{cr} + a_{ijl}^{se\times cr}$ is sufficiently large relative to a_{ij}^{se}, the consumer is a quality *l* regular for product *j*.

Moreover, if a_{il}^{cr} is sufficiently large relatively to $a_{ijl}^{se\times cr}$ for all *j*—that is, if the consumer mostly values the credence attributes associated with the quality label *l*—and $U_i(.)$ is such that the consumer preferences exhibit some taste for product variety, one should expect the quantities of purchased food items of quality *l* to be positively correlated across products. If, to the contrary, the consumer mostly values the credence attributes when they are associated with a specific subset of search and experience attributes–corresponding to $a_{ijl}^{se\times cr}$ being much larger than a_{il}^{cr} for a few values of *j*, one should expect little correlation between the purchased quantities of products of quality *l*.

3.2.2. Distribution of quality-food consumption

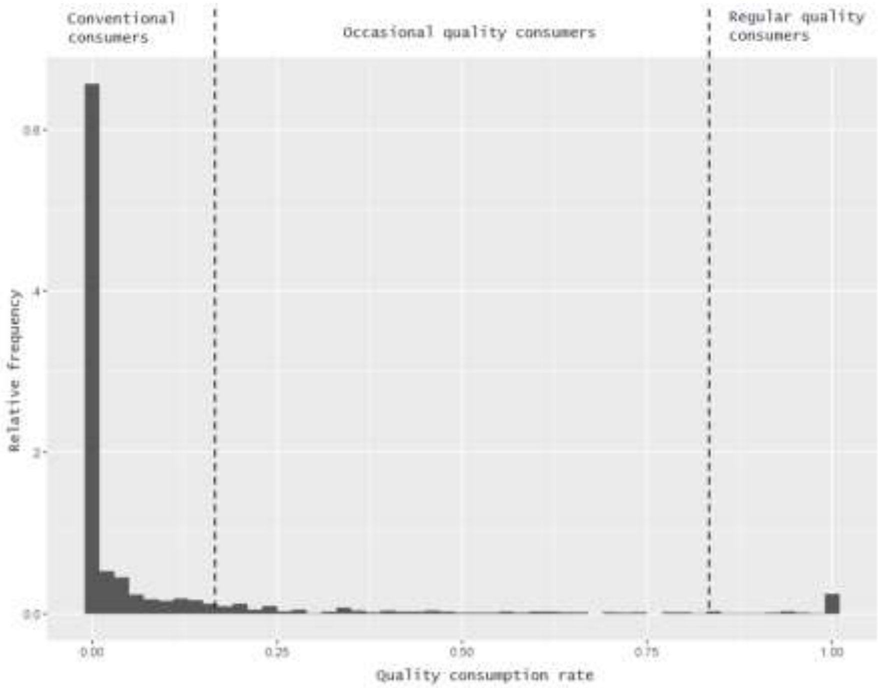
We first investigate regularity by analyzing the distribution of the quality consumption rate of a given product, i.e. the ratio of purchases of the quality version of the product over the total number of purchases during the time span the household remains observed in our dataset. Individuals who almost never buy the quality version of the product are characterized by a quality consumption rate close to 0. They are said to be ‘conventional regulars’; those who mostly purchase the quality version (i.e., quality consumption rate close to 1) are said to be ‘quality regulars’.

The first part of our investigation is organized around the three following hypotheses:

- For a given product, consumers are regulars: they either purchase mostly its conventional version or its quality version, but not a mix of both (H1);
- Quality regular consumption is consistent across the food basket: a consumer who is a *quality regular* for a product is a *quality regular* for an important part of his food basket (H2);
- The total turnover of quality products purchased by regulars is substantial (H3).

If H1 holds true, the distribution of the quality consumption rate among the sample should be bimodal, with a mode around 0 (conventional regulars) and another around 1 (quality regulars). Figure 1 illustrates such a case. The dashed lines represent the two thresholds under and above which a consumer is considered as a conventional or organic regular, respectively.

Figure 4. Bimodal distribution and classification of quality-food consumers



Following (Silverman, 1981), it is possible to test if the density of a distribution has more than k modes using kernel density estimation. Indeed, the kernel density estimate for window width h based on the observations $X_1,...,X_n$ is defined by

$$f(t,h) = n^{-1}h^{-1}\sum_{i=1}^{n} K\{h^{-1}(t - X_i)\}, \tag{2}$$

where K is the normal density function in our case. The window width h is a parameter controlling to which extent the observations are smoothed in order to obtain the kernel estimate and t is the endogenously estimated mean of the kernel. If the data is multimodal, a large value of h will be needed to obtain a unimodal kernel estimate.

The test relies on the comparison between the estimated h for a unimodal distribution and h_{crit}, the k-critical window width, defined as:

$$h_{crit} = min\{h, f(.,h)\ has\ at\ most\ k\ modes\}.$$

The lowest h_{crit} gives the most likely number of modes for the distribution. Using the Silverman test, we can thus test whether the distribution of quality-food consumption is bimodal for each product and product family.

To test H2, we define three types of behavior toward quality and organic food, illustrated in Figure 1:

- *conventional regulars*, who are almost never buying the quality version of a product (0-20% of quality purchases for a given product);
- *quality-food regulars*, who are almost always buying the quality version (more than 80% of quality purchases for a given product);
- and *occasional quality-food consumers* (20-80% of quality purchases for a given product).

The 20% and 80% thresholds are partly arbitrary. However, when a beta distribution is fitted to the organic consumption rate of products with a bimodal distribution, around 90% of the values are either above or below these thresholds (see Supplementary Materials (SM) 1 for the detailed procedure). Through this typology, we also assess the duplication of quality consumption behavior across different products (H2): if I am an organic regular for eggs, am I likely to be an organic regular for milk? (see (Monier et al., 2009) for an example of this question in a two-products case).

3.2.3. Determinants of the probability to be a regular organic consumer

In a second step, we assess which product attributes or household characteristics influence whether a quality-food consumption (*i*th consumer x *j*th product) is regular. Because no regular behavior is identified for geographical indications and *label rouge* products (see section 4.1.1), this second step is restricted to organic products. We use the random utility discrete choice framework (McFadden, 2001) as an application of the theoretical model. In this model, the utility function is assumed to be well-behaved (preferences are complete, reflexive and transitive) and known by the consumer. Thus, the consumer can compare the organic and conventional alternatives of a product and rank them in order to purchase the product that maximizes his utility. However, some parts of the utility function, essentially the preference for the credence attributes *per se*, cannot be separated from other elements in scanner data. This is why the random utility model is used here to identify which product attributes or household characteristics influence quality-food regularity rather than a structural estimate of the coefficients in equation (1) of our theoretical framework. The random utility model describes the utility (U_{ijo}) of the *i*th consumer purchasing the *j*th product in its organic version as the sum of the observed attributes (V_{ij}) and a random component (ε_{ij}):

$$U_{ijo} = V_{ijo} + \varepsilon_{ijo} \quad (3)$$

Similarly, the utility (U_{ijc}) of the conventional product *j*'s choice is described as:

$$U_{ijc} = V_{ijc} + \varepsilon_{ijc} \tag{4}$$

The *i*th consumer will be an organic regular for the *j*th product at time *t* if $U_{ijo} > U_{ijc}$ and the probability that this consumer will be an organic regular can be written as:

$$P(Y_{ijt} = 1) = P(U_{ijto} > U_{ijtc}) = P(\varepsilon_{ijtc} - \varepsilon_{ijto} < V_{ijto} - V_{ijtc}) = P(\varepsilon_{ijt} < V_{ijto} - V_{ijtc}) \tag{5}$$

where Y_{ijt} is a binary choice variable:

$$Y_{ijt} = \begin{cases} 1 \text{ if the } i\text{th consumer is an organic regular for the } j\text{th product at time } t \\ \qquad 0 \text{ otherwise} \end{cases}.$$

Defining $f(\varepsilon_i)$ as the density function of ε_i, (3) becomes:

$$P(Y_{ijt} = 1) = \int_{\varepsilon} Z_{ijt}(\, \varepsilon_{ijt} < V_{ijto} - V_{ijtc}) g(\varepsilon_{ijt}) d\varepsilon_{ijt}, \tag{6}$$

where Z_{ijt} is a binary variable indicating if the term inside the parenthesis is true $(Z_{ijt} = 1)$ or false $(Z_{ijt} = 0)$, i.e. if the utility derived from the regular organic choice exceeds the one from the conventional choice. Furthermore, Z_{ijt} can be empirically described as depending on the *i*th consumer characteristics and the *j*th product attributes at time *t*. Because most households remain in the panel for several years – on average 5 years – a random household effect is introduced to correct for the within-household correlation in the error terms:

$$Z_{ijt} = \beta X_{ijt} + u_i + \varepsilon_{ijt} \tag{7}$$

where $X_{ijt} = (x_{ijt1}, \dots, x_{ijtk})$ is a matrix of variables explaining the choice of being a regular organic consumer, i.e. they represent the *j*th product attributes (price ratio between the organic and the conventional version, a binomial variable indicating if the product is processed or not, the type of shop where the product is bought…) or the *i*th consumer characteristics (age of children, income, size of the city in which they live, their socio-professional category…), $\beta = (\beta_0, \beta_1, \dots, \beta_k)$ is a vector of parameters to be estimated, ε_{ijt} captures the idiosyncratic residuals and u_i is a random effect related to the *i*th household, accounting for the unobserved heterogeneity of the households and the correlation among the ε_{ijt}.

To estimate Eq. (7) with scanner data, we assume that ε_{iit} follow a logistic distribution and thus that ε_{ijtc} and ε_{ijto} are identically and independently distributed as type I extreme value (Onyango et al., 2007). This hypothesis on the distribution of the errors terms may sometimes be violated in empirical analysis, as the unobserved portion of utility, captured by the errors terms, can be correlated among the different consumer x product couples, but the potential induced bias is limited (Train, 2003). Under this assumption, $P(Y_{ij} = 1)$, the probability that the consumer *i* is an organic regular for the product *j* is given by the following logit model:

$$P(Y_{ij} = 1) = F(Z_{ij}) = F(\beta X_{ijt} + u_i) = \frac{1}{1+\exp(-\beta X_{ijt}+u_i)}. \tag{8}$$

Furthermore, we construct two other logit models, one—Logit Product—using only the information on the product attributes and the other—Logit Household—using only the variables describing the consumers' characteristics. Using a likelihood ratio test, we then compare the goodness of fit of these two models, in order to assess which set of characteristics—products' vs households'—is the most important driver of regular organic behavior.

We repeat the analysis on a restricted sample containing only households who purchased at least 20% the product of interest as organic. This allows to examine whether the same variables are correlated to the probability of being a regular organic consumer for a product, compared to being either a conventional or occasional consumer (called thereafter "full sample logits") or to the probability of being a regular organic consumer compared to being an occasional consumer only ("restricted sample logits").

3.3. Data

This paper uses French data from Kantar WorldPanel which contains food-at-home purchases of French households. For the analysis, we use the number of organic, quality and conventional products purchased, filtering out households who bought less than three times the considered products. To define the product families (level 1, 23 families), the classification from (Boizot-Szantai et al., 2017) is reused, with more detailed groups for fruits and vegetables. We also created a more in-depth classification (level 2, with 237 categories/products), which differentiate each fruit and vegetable (carrots, potatoes…) and types of meat (pork, beef…). In this panel data, we also have socio-economic information on 12,453 yearly active households, surveyed one or several years from 2011 to 2016 (5 years on average) whose descriptive statistics are presented below (Table 1). In addition, a map of the spatial distribution of our sample in France is available in SM 3.

Table 3. Descriptive statistics of the households in the sample (relative frequencies)

Years		Children		Professions and socio-professional categories		City		Family status		Income category	
2011	15.0%	No children	67.7%	Managers, shopkeepers and heads of companies	34.3%	City of less than 2000 inhabitants	27.7%	Couple	61.8%	Superior middle income	39.9%
2012	14.9%	Youngest child <25 month	5.5%	Farmers	0.8%	City of 2000-4999 inhabitants	6.9%	Single	38.2%	High income	48.5%
2013	15.3%	Youngest child >25 months and <5 years	7.9%	Managers and superior professions	9.1%	City of 5000-9999 inhabitants	6.0%			Inferior middle income	9.3%
2014	17.8%	Youngest child >6 years and <10 years	10.3%	Employes	20.9%	City of 10 000-19 999 inhabitants	5.5%			Low income	2.3%
2015	16.5%	Youngest child >11 years and <15 years	8.7%	Manual occupations	16.2%	City of 20 000-49 999 inhabitants	6.7%				
2016	20.5%			Intermediate professions	15.2%	City of 50 000-99 999 inhabitants	6.6%				
				Retired	1.8%	City of 100 000-199 999 inhabitants	4.7%				
				Unemployed, student	1.6%	City of more than 200 000 inhabitants	20.2%				
						Paris agglomeration	15.7%				

As shown in the introduction, the organic products' availability and their price differences compared to conventional versions are presented as key drivers of organic consumption.

However, in the recent literature on organic consumption, availability is most often neglected. In order to assess the role of product availability on consumption behavior, an indicator of the availability of quality-food—organic, *Label Rouge* or geographical indications—is developed for each consumer. This indicator is the share of shops which offer the quality food of interest out of all shops where the household is usually shopping and the exhaustive results are available in the Supplementary Data (available online in the published version of the paper). It is computed after the following steps:

For each household, we define the set of shops where it is usually shopping as the shops where the household went at least three times.

For each shop, we estimate that a given quality product is available if it has been purchased by at least one household in a shop of the same retail chain, same size (hypermarket/supermarket) and in the same region. These three variables are indeed the most important in predicting the availability of organic products: together, they explain 68% of the variance in the number of organic items available for online purchase in the Burgundy region (see SM 2 for details on data collection and regression).

At shops where there are few purchases for a given product, the absence of organic purchases may be an artefact caused by data scarcity rather than actual unavailability. These shop x product combinations are filtered out as "no data" to avoid false negatives. For this purpose, the act of buying an organic product in a given shop is assumed to follow a binomial law using the nationwide average share of organic purchases for this product as its probability of success. We determine the critical (minimal) sample size, for a given significance level of 0.05 and a power level of 0.8, for which the hypothesis that the product is available but has not been purchased can be rejected.

Then, if the observed number of purchases of a product is above the critical sample size and if the organic version has never been purchased, we can assert that the organic version of the product is not available. However, if the organic version has been purchased at least one time, we directly assess that it is available in the shop considered.

The indicator of availability for each household is then defined as the proportion of shops offering the organic product among all shops in which the household purchases food. The indicator ranges between 0—the organic version of the product is never available to the household, and 1—the organic version of the product is available in all the shops the household attends to.

Similarly, we develop a price ratio indicator (organic price per kg divided by conventional price per kg) between organic and conventional versions of a same product, which varies depending on the region, the shop and the product considered. In addition, we create an absolute price difference indicator (organic price per calorie – conventional price per calorie, the harmonization per calorie making it comparable across product families).

3.4. Results

3.4.1. Bimodality of quality-food consumption at different aggregation levels

3.4.1.1. Consumption behavior of geographical indications and *label rouge* products is occasional

For the few products for which information on quality purchases other than organic is available (labelled meat, fish, eggs, processed meat and cheese), these quality purchases are not bimodally distributed, with the exception of processed meat (*label rouge* and PDO matured ham) which has a mode above 80% of quality purchases (Table 2). It must be noted that *label rouge* and PDO/PGI information are lacking for some products (i.e. meat, where certification information is available for chicken only). Consumers thus buy these products as exceptional purchases, possibly for special occasions. H1 is therefore invalidated for geographical indications and *label rouge,* and so is H2. Moreover, only 3% of the market value of these certified products is purchased by regular consumers, which invalidate H3 (for an example, see Table 4). As geographical indication and *label rouge* products are not subject to regular consumption, we do not perform the second part of the analysis (estimation of the determinants of regular consumption) for them.

Table 4. Distribution of the quality labels (PDO, PGI, label rouge) consumption per product family

	Nb of bimodal categories	Nb of unimodal categories	Nb of multimodal regular categories	Nb of multimodal not regular categories
Meat (Chicken only)		2		
Processed Meat	2	3	2	2
Seafood		2		
Eggs		1		
Cheese		1		

Unimodal = single mode (no regular behavior or only conventional regulars) / Bimodal = two modes with one lower than 20% and the second higher than 80% (regularity, either conventional or quality-food) / Multimodal regular = at least three modes, including one higher than 80% (existence of all consumer types: conventional regulars, occasional and quality regulars) / Multimodal not regular = at least three modes, none higher than 80% (no quality regulars).

3.4.1.2. Organic regulars are consistent for a given product, but not among product families

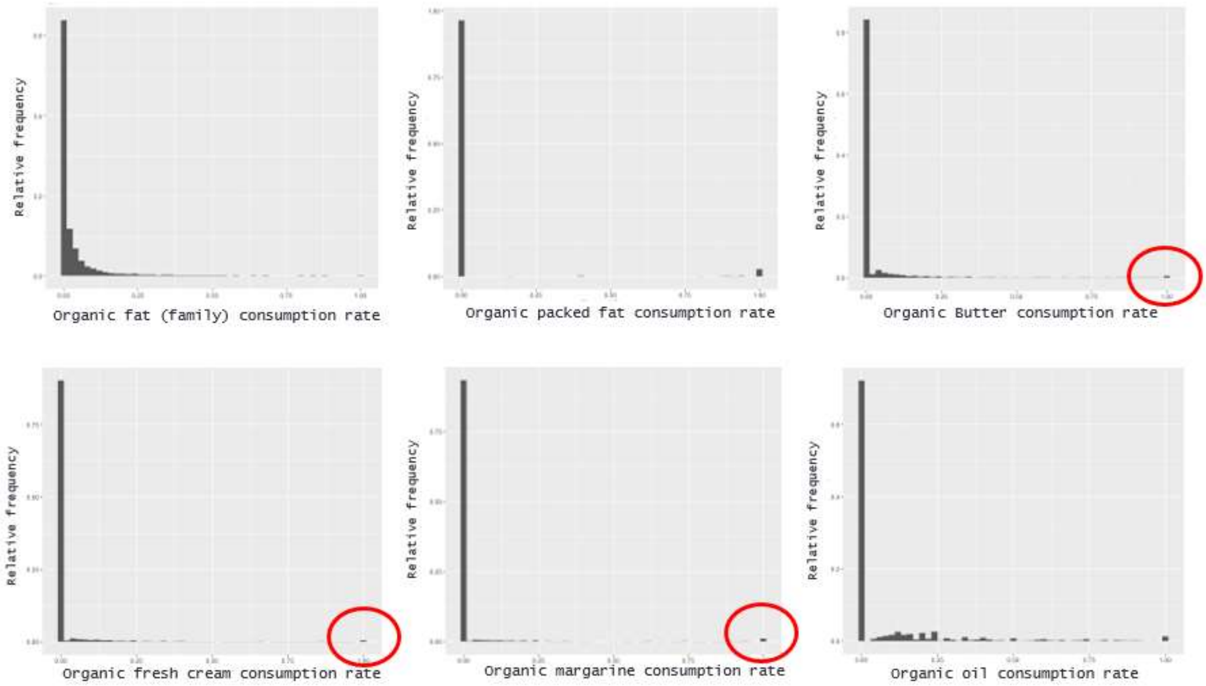
56% of the 23 families of products are subject to regular behavior from a significant share of consumers (Table 3): 35% of distributions are bimodal and 21% are multimodal with one mode in the 80-100% range). However, the rationale for agglomerating products into families is not necessarily suited to assess the consistency of consumer behavior. Indeed, consumers are more consistent at the product level (for exhaustive results see the SD 2 and 3): 80% of products are subject to regular behavior from a significant share of consumers (bimodal (44%) or multimodal with a mode in the 80-100% range (36%)). For example, the distribution of the organic fat product family is not bimodal while a deeper look at the distribution of the 5 products categories composing this family shows that 3 fat products categories have a bimodal organic consumption distribution (Figure 5). H1 is therefore validated for organic products.

Table 5. Distribution of the organic consumption per product family

	Nb of bimodal distributions at product level	Nb of unimodal distributions at product level	Nb of multimodal distributions with one mode higher than 80%	Nb of multimodal distributions without mode higher than 80%	Family distribution
Alcoholic beverages	1	1	3	3	Multimodal regular
Appetizers	0	0	3	0	Multimodal regular
Baby foods	4	0	2	0	Bimodal
Biscuits, cakes and pastry	1	0	3	0	Unimodal
Bread, flour	1	0	1	1	Bimodal
Cheese	1	1	1	0	Unimodal
Confectionary products	2	1	2	2	Unimodal
Culinary ingredients	11	2	11	2	Unimodal
Desserts	0	0	1	0	Bimodal
Eggs	1	0	0	0	Bimodal
Fat	3	0	1	1	Unimodal
Fresh F&V	45	3	20	6	Unimodal
Hot drinks	1	0	2	1	Unimodal
Prepared Meal	2	1	3	0	Multimodal regular
Meal substitutes	2	0	0	0	Bimodal
Meat	0	0	3	2	Unimodal
Milk	1	0	1	0	Bimodal
Non-Alcoholic beverages	0	1	2	0	Unimodal
Processed F&V	24	1	7	8	Unimodal
Processed Meat	3	1	10	5	Bimodal
Seafood	0	0	4	2	Multimodal regular
Starchy foods	0	1	3	1	Unimodal
Sweeteners	1	0	3	0	Multimodal regular

Unimodal = single mode (no regular behavior or only conventional regulars) / Bimodal = two modes with one lower than 20% and the second higher than 80% (regularity, either conventional or quality-food) / Multimodal regular = at least three modes, including one higher than 80% (existence of all consumer types: conventional regulars, occasional and quality regulars) / Multimodal not regular = at least three modes, none higher than 80% (no quality regulars).

Figure 5. Distribution of the organic consumption of fat products



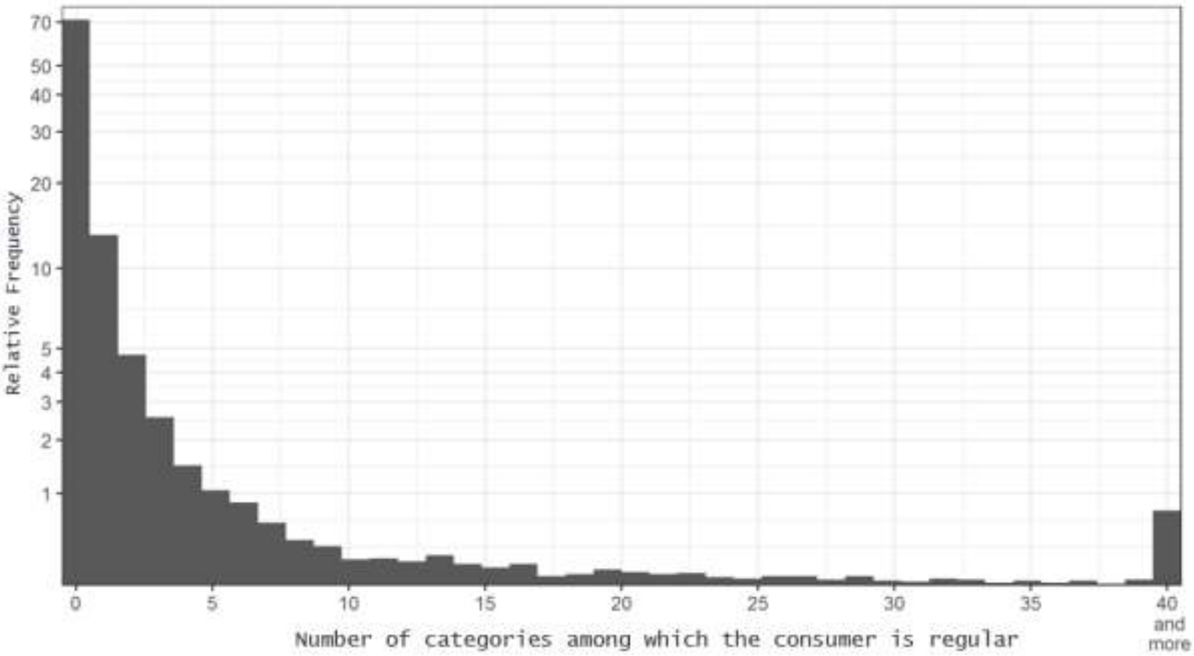
3.4.1.3. The basket of organic regulars remains dominated by conventional products

Even if the existence of organic regulars can be observed for 80% of food products, the consumers that purchase several products as organic regulars are scarce. More than 71% of our sample does not buy any product as organic regulars and only 6% purchase more than 5 products as organic regulars (see SD 4 for exhaustive results). The consumers in our sample purchase on average 80 different products. This shows that most consumers have a regular organic behavior for only a few products (Figure 3). Thus, regular organic behavior is not very consistent across products and H2 is invalidated (Marian et al., 2014).

In our theoretical framework, this indicates strong interaction effects in the consumer utility function (Eq. (1)) between the organic (credence) attribute of a product and the search and experience attributes (roots vegetables, fruits growing in a tree …). In product families compounded of many categories such as fresh Fruits and Vegetables (F&V), the regular organic behavior seems coherent among very similar products (quasi-substitutes, e.g. lemons and oranges), but not among modestly close products (e.g. carrots and onions). The interaction effect could therefore reveal itself for search and experience attributes slightly more generic than the product level, but certainly more specific than the product family level.

There is however a non-negligible category of consistent regulars: 0.8% of consumers are organic regulars for more than 40 products, that is half of the average basket, noting that many minor products are often not available at all under the organic label. For this consumer category, the appetence for the credence attribute per se is strong (a_{il}^{cr} >> $a_{ijl}^{se\times cr}$) in our theoretical framework). This consumer category represents 3% of all regulars for at least one product.

Figure 6. Distribution of the number of categories for which consumers are organic regulars



The number of categories is log-transformed and bound at 40 to increase the visibility of the plot.

3.4.1.4. 28% of the organic market is purchased by regular consumers

The share of the organic market in France purchased by organic regulars averages at 28%, which tends to validate H3. However, this average is heavily influenced by the market values of the products, which strongly differs between product families. For example, the market for organic wine is five times larger than the one of organic broccolis, but the share of the organic market purchased by regulars is only 8% for wine compared to 75% for broccolis. Thus, the size of the market and the unit values of products strongly drive down the average share of the organic market purchased by regulars. Among the detailed results, 40%, 33% and 43% of the organic eggs, organic F&V and the organic milk markets are purchased by regulars, respectively (Table 4).

Table 6. Examples of the organic market share represented by regular consumers (exhaustive results are available in SD 2)

		Share of the consumers	Share of organic market	Average frequency of organic purchases
Eggs	Conventional regulars	85%	10%	2%
	Occasional consumers	11%	50%	44%
	Organic regulars	4%	40%	92%
Milk	Conventional regulars	90%	11%	2%
	Occasional consumers	7%	46%	43%
	Organic regulars	3%	43%	92%
Label rouge raw ham	Conventional regulars	63%	20%	0.6%
	Occasional consumers	35%	72%	38%
	Quality regulars	2%	8%	90%

3.4.2. Determinants of regular organic consumer behavior

3.4.2.1. Product availability and product family are key determinants

Table 7. Selected results of the Logit models

	Full Logit	Full Logit Household	Full Logit Products	Restricted Logit	Restricted Logit Household	Restricted Logit Products
	(1)	(2)	(3)	(1)	(2)	(3)
Hard-discount	0.453***		0.427***	-0.097		-0.104
	(0.063)		(0.063)	(0.064)		(0.064)
Hypermarket	0.557***		0.548***	0.197***		0.203***
	(0.044)		(0.044)	(0.046)		(0.046)
Organic Shop	3.360***		3.357***	1.809***		1.813***
	(0.052)		(0.052)	(0.051)		(0.051)
Retailer brand	0.817***		0.815***	0.704***		0.705***
	(0.024)		(0.024)	(0.027)		(0.027)
Price ratio between organic & conventional	0.018		0.017	0.181***		0.182***
	(0.015)		(0.015)	(0.033)		(0.033)
Absolute price difference between organic & conventional	0.031*		0.031*	-0.101		-0.101
	(0.016)		(0.016)	(0.079)		(0.079)
Youngest child <25 month	0.065	0.232***		0.030	0.094	
	(0.078)	(0.076)		(0.074)	(0.072)	
Youngest child >11 years and <15 years	-0.072	-0.128*		0.015	-0.022	
	(0.071)	(0.069)		(0.070)	(0.068)	
Managers and superior professions	0.325***	0.315***		0.153**	0.205***	
	(0.086)	(0.085)		(0.074)	(0.073)	
Manual professions	-0.326***	-0.267***		0.035	-0.052	
	(0.077)	(0.077)		(0.069)	(0.068)	
Retired	-0.241	-0.223		-0.246	-0.203	
	(0.192)	(0.195)		(0.166)	(0.168)	
City of 5000-9999 inhabitants	0.081	0.113		-0.012	0.012	
	(0.119)	(0.121)		(0.099)	(0.099)	
City of more than 200 000 inhabitants	0.330***	0.335***		0.066	0.158**	
	(0.078)	(0.079)		(0.063)	(0.064)	
Paris agglomeration	0.191**	0.180**		-0.066	0.065	
	(0.088)	(0.089)		(0.071)	(0.070)	
Single	-0.170***	-0.109**		-0.100**	-0.130***	
	(0.053)	(0.051)		(0.050)	(0.049)	
High income household	0.109**	0.090*		-0.052	-0.027	
Low income household	-0.183	-0.170		-0.155	-0.111	
	(0.172)	(0.174)		(0.148)	(0.146)	
BMI	-0.198***	-0.216***		-0.020***	-0.031***	
	(0.028)	(0.028)		(0.006)	(0.006)	
Availability	0.335***		0.340***	0.574***		0.576***
	(0.016)		(0.016)	(0.069)		(0.069)
Baby foods	0.884***		0.911***	0.610**		0.634**
	(0.266)		(0.266)	(0.287)		(0.286)

Bread, flour	0.826***		0.826***	0.547**		0.547**
	(0.255)		(0.255)	(0.274)		(0.274)
Eggs	2.283***		2.284***	1.992***		1.998***
	(0.052)		(0.052)	(0.058)		(0.058)
Meat	0.101		0.103	0.198		0.202
	(0.128)		(0.128)	(0.129)		(0.129)
Milk	2.496***		2.496***	2.321***		2.327***
	(0.053)		(0.053)	(0.060)		(0.060)
Processed F&V	0.159		0.161	0.381		0.380
	(0.256)		(0.256)	(0.277)		(0.277)
Starchy foods	0.283		0.283	0.186		0.186
	(0.256)		(0.256)	(0.275)		(0.276)
Processed Product	0.318 (0.250)		0.317 (0.250)	0.257 (0.269)		0.260 (0.269)
Constant	-8.753***	-6.666***	-8.276***	-3.569***	-2.223***	-3.397***
	(0.174)	(0.077)	(0.062)	(0.161)	(0.065)	(0.060)
Number of households	12453	12453	12453	8854	8854	8854
Household random effect's standard deviation	2.162	2.222	2.228	1.162	1.174	1.207
Observations	1,221,430	1,221,430	1,221,430	70,549	70,549	70,549
Log Likelihood	-47,362	-53,323	-47,493	-31,058	-33,801	-31,084
Akaike Inf. Crit.	94,858	106,714	95,071	62,251	67,670	62,255

Notes: ***, **, * Significant at the 1, 5, 10 percent levels respectively. The values between brackets refer to the standard deviation of the coefficients. This table presents a selection of the variables used in the models based on their interests for the discussion. The exhaustive results are available in SM 4.
Retailer brand is a dummy that takes the value 1 if more than 50% of the purchases of a product where from the retailer brand.
A household of 4 members is considered of low income if its monthly income in under 2094€ and of high income if its monthly income is above 5808€.

Dummy variables	Reference level
Shop type	Open-air market
Youngest child	No children
Working occupation	Artisan and craftsman
Size of City	<2000 inhabitants
Economic status	Superior middle income
Product family	Fresh F&V

The logit model on the whole sample (Table 5, model 1) shows that regular organic behavior is more likely to occur when a consumer makes most of its purchases for a given product at a specialized organic store and if he purchases the organic product from the retailer brand. The price ratio between the organic and conventional versions of product is not significantly correlated with the probability of being a regular organic consumer while the absolute price difference between the two versions is positively correlated with it: a higher the price difference is associated with a higher share of organic regulars.
The typical organic regulars are single, without children and have a lower Body Mass Index (BMI), indicating that they have a healthier diet or practice more physical activities. They usually also have a high income, a managerial or superior professions or are own-account workers and live in large cities. However, consumers living in rural areas (reference level) are more likely to be organic regulars than the ones livings in small cities.

The logit regressions reveal that some product families are more likely to be purchased by organic regulars than others: baby foods, biscuits, cakes and pastry, bread and flour, confectionary products, desserts, eggs, fat, beverages, meal substitutes, milk, sweeteners, processed F&V and starchy food. The availability of the organic version of a product in the shops the consumers usually visit appears as a significant driver of regular behavior.

When using a smaller sample, compound of occasional and regular organic consumers only, the results are similar (Table 5, model 4). Nevertheless, in these restricted logit models, the role of prices differs: when comparing occasional and regular organic consumers, a higher price ratio between organic and conventional products is associated with a higher probability of being a regular consumer whereas the correlation with the absolute price difference becomes non-significant. In addition, in all logit models, the standard deviation of the households' random effect is high, of comparable size with the largest treatment effect (eggs family), which show an important household-related variability of the probability of being an organic regular.

3.4.2.2. Products' attributes matter more than households' characteristics

Two other logit models are also computed, one using as predictor variables the information related to the products only (price ratio, frequency, processed or not…) and the other using the information on the household only (number of children, wealth, professional status…). Performing a Likelihood Ratio test, we conclude that the model using product informations predicts better the regular consumer behavior (Table 6). These results still stand when using the restricted sample of occasional and regular organic consumers.

Table 8. Likelihood Ratio tests between the models of product attributes and household characteristics, whole sample

Model	Numbers of Variables	LogLikelihood Value	Logit prediction accuracy	Sensitivity	Specificity
Logit Full	60	-47,362***	98.9%	69%	99%
Logit Products	36	-47,493***	98.9%	69%	99%
Logit Household	24	-53,323***	98.7%	60%	99%
Restricted Logit Full	60	-31,058***	82.3%	72%	84%
Restricted Logit Products	36	-31,084***	82.1%	72%	84%
Restricted Logit Household	24	-33,801***	79.6%	67%	82%

***Likelihood ratio test significant at the 1 percent level.

3.5. Discussion

3.5.1. Strong interrelation between credence and search & experience attributes in determining regular organic consumption.

The first part of this paper, focusing on the bimodality of organic consumption, outlines the product families for which regular consumer behaviors can be found: hot drinks, milk, eggs, baby foods, meal substitutes, desserts (which include dairy products) and bread and flour (Table 5). The results are confirmed by the logits on regular organic behavior, in which these products families have positive regression coefficients (Table 7). Except F&V and starchy food, these product families are the most purchased ones in the organic market (Agence Bio, 2019b; Hill and Lynchehaun, 2002). Clearly, product availability plays a role: product families that are difficult to find organically in conventional supermarkets (meat or seafood for example) are not dominantly subject to regular consumption behavior: their share of organic purchases is unimodal. Also, the fact that some product families are compound of more products than others (for example, fresh F&V family has 71 products while milk has only two) influence the distribution of organic consumption, as shown in Figure 2. Moreover, the characteristics of organic products (price, quality, availability) likely vary between outlets. Consumers are likely to be influenced by the choice offered at the outlet where they shop most often, which may explain why consumers who mostly shop at specialized organic shops are more likely to be regulars than those shopping mostly in hard discounts. Moreover, all consumers do not have access to all outlet brands, depending on where they live. The availability indicator that we develop captures this disparity and appears as a key variable in the logit regressions on regular organic behavior (Table 5). Indeed, a lower availability of organic products compared to conventional ones is correlated with a lower organic consumption (Buder et al., 2014; Dimitri and Dettmann, 2012; Massey et al., 2018).

In the same sense, very few consumers are organic regulars for a large number of product categories, as only 6% of them purchase as regular more than 5 product categories and only 0.7% of them have a regular behavior on more than 50% of the products they purchase (Figure 3).

Following our theoretical framework, the most likely interpretation of this result is a strong interaction effect between the credence attribute (the product is organic) and the search and experience attributes (the product is an apple) in the consumer utility. Most consumer do not value much the organic sign *per se*, but they value it strongly for a few specific products. Relating that to the dominant health driver of organic consumption (Buder et al., 2014; Padel and Foster, 2005), a possible explanation is that consumers are mostly concerned about the healthiness of a few specific products, e.g. because they have seen a documentary on the amount of pesticides in lemon or read a newspaper article on the amount of antibiotics in milk. Accordingly, they may become organic regulars for these specific products, for which they received health information, but this change may not spillover on their broader feeding routines.

However, at least two other reasons can explain this weak consistency of regular behavior across products. The first is again availability, as some products can only be found in specialized shops, but most of the consumers purchase food in several types of shops (conventional supermarket, open air market, specialized shops…). As the logit results show, if a product is mainly purchased at a specialized shop, the probability that the consumers will follow a regular behavior increases drastically. So, as consumers shop in different outlets, even if they choose to be regulars on some products that they usually purchase at their main shopping source, they may have to buy these products in others shops (supplemental purchases, oblivion, unexpected meal to prepare…) but the organic versions of these products may be unavailable, more expensive or of a lesser quality and they will not purchase it. This interpretation is supported by the lower numbers of regulars found when the analysis is based on frequency (number of purchases) rather than volumes (liters or kilograms). Indeed, supplemental purchases weigh more on the shares of organic purchases when computed with frequencies. For the F&V family for example, we find that more households following a regular organic behavior for at least one product when the shares are computed with quantities (1548 households) than in frequencies (1303 households). Similarly, the number of F&V categories purchased by regular organic households is larger when they are computed in quantities (3317) than frequencies (2614).

The second reason is that the data we use is collected at the household level, and even if the main shopper is identified, there can be another shopper (husband/wife, teenagers…) that also sometimes purchases food. This occasional shopper may not have the same purchasing behavior or may not go to the same shopping source, and thus the household may not be regular even though each of its members are regulars of different styles. This effect seems weak however: couples are more likely to be organic regulars than singles (Table 5).

Finally, consumers are more likely to be organic regulars if they purchase products from retailer brands, which are generally cheaper than other organic brands (Ngobo, 2011). However, the price ratio between the organic and conventional version of a product is not significantly correlated with regular behavior, only the absolute difference in prices is significantly, and positively, associated with regular organic consumption. This surprising result—i.e., the more expensive the organic version of a product is, compared to the conventional version, the more likely the consumer will be an organic regular—can be understood as a weak price-elasticity of regular consumers to organic products prices. Indeed, if a consumer is an organic regular, most likely for health consideration, he will not be as reactive to the relative price of organic products as occasional or conventional consumers. This result is strengthened by the restricted logit models, in which the regression coefficient of the relative price of organic is positive and significant.

3.5.2. The characteristics of actual organic regulars are similar to those of "declared" pro-organic consumers

The description of regular organic consumers which can be drawn from the logit models is comparable with the main findings of the literature on the socio-economic characteristics of organic consumers (Kesse-Guyot et al., 2013). Indeed, we corroborate that regular organic consumers have a higher income, are more urban and have a higher profession position than non-regular organic consumers (Table 5). Comparing regular consumers with occasional consumers only, we uncover that regular consumers are more represented in the upper-middle class and high professional status (Table 5).
Nevertheless, the comparison of the logit models with product attributes to the logit models with household characteristics only demonstrates that product attributes explain better regular organic behavior than the household characteristics (Table 6).

3.5.3. Public Policy implications: product-specific targets

Of course, what matters most to policy makers is the total amount of organic production produced and sold, relatively to conventional production and the negative health and environmental externalities associated with it. However, an increase of organic production can be reached by sustaining organic consumption, which is currently done by French policies ("Ambition Bio 2022", "Egalim" law in 2018). Our results from the analysis of organic consumers and their regular behavior advocate for more product-specific policies. Indeed, as much as 28% of organic value is purchased by households with a regular consumption pattern for a few specific products. Accordingly, public initiatives aiming at increasing organic consumption should focus both on promoting the organic label *per se* and on promoting specific organic products. They may also promote a "regular" attitude towards some organic products—e.g. "remove pesticides from your morning orange juice: buy organic oranges". Targeting product families for which a regular consumption behavior is already frequent may be particularly promising, as regular organic consumption exists (H1 is validated) but is not yet very consistent across the food basket (H2 is invalidated). This is supported by our finding that product characteristics explain better the regular organic behavior than the household characteristics (Table 6). If there is a choice to be made between targeting specific products or specific consumers, one should go for specific products although some consumer segments—higher income, higher professional status and more urban—are likely to be more receptive (Apostolidis and McLeay, 2016).
Geographical indications and *label rouge* products on the other hand are purchased occasionally, making them somewhat comparable to luxury products. Marketing and promotion actions for these products may therefore want to get inspiration from non-food luxury products.

3.6. Conclusion

This paper demonstrates that quality-food with similar market shares can be subject to widely different consumption behaviors. Consumption of geographical indications and label rouge is always occasional while consumer attitude towards organic food is often regular: for a given product, some consumers tend to either purchase it always organic or always conventional. Indeed, conversely to previous studies using scanner data or surveys, we use observable information, the distribution of quality purchases, to categorize regular and occasional quality consumers. Doing so leads to a better comprehension of quality consumers' behavior, i.e. that an important part (29% of our sample) is regular for at least one organic product, but that regular organic consumers for their whole food basket are scarce. Moreover, regular organic consumers purchase 28% of the total value of the organic market and up to 50% for some F&V, eggs or milk. In this sense, public policies should target product categories instead of the whole food basket and develop organic regular behavior, using as levers the product attributes and household characteristics our analysis revealed as strongly related with regular organic consumption. However, other quality products, such as Geographical Indications, are purchased as extraordinary goods and so policies aiming at increasing their consumption should relate to those on luxury goods.

More precisely, we illustrate that the main product families for which organic consumption distributions are bimodal, i.e. for which regular consumer behaviors can be found, are eggs, milk, baby food, meal substitutes, desserts, bread and flour. When organic consumption is analyzed at product level, one sees that its distribution is bimodal also for most fruits and vegetables (processed or raw).

Besides, households which exhibit regular organic consuming behavior are richer, more urban, have a higher professional status than the others. These organic regulars also have a higher propensity to be in couples and to have fewer children.

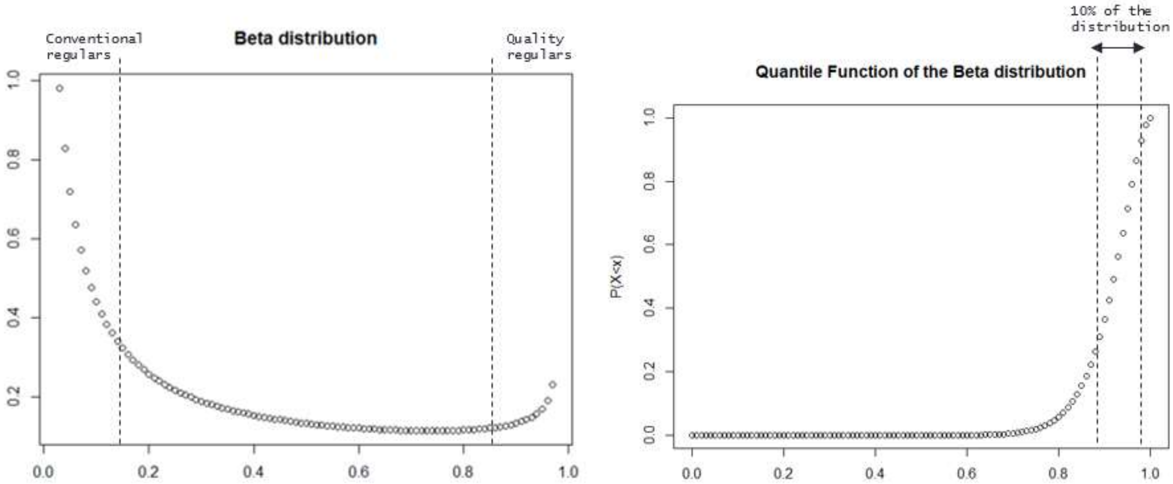
The products categories that are consumed by organic regulars are more available and organic regulars do not seem to be influenced by the price of organic products. To the contrary, a higher price difference between an organic product and its conventional counterpart is associated with a higher share of organic regulars, possibly because organic regulars are willing to buy the organic alternative at all costs. Moreover, product attributes explain better organic regular behavior than household characteristics. Further research may explore the interaction effects in the consumer utility function between the organic attribute and other product attributes (thickness of skin for fruits, roots vegetables…). Computing price and income elasticities of quality-food products would also shed light on consumer behavior, especially in defining which products are luxury goods. Lastly, bridging the gap between organic production and consumption may help designing efficient policies: in light of our work, policies could focus on securing the regular consumption of products whose production in organic systems has high environmental or health value-added (production nearby water catchments for example).

3.7. Supplementary Materials

SM 1. Statistical determination of the regular behavior thresholds

In our empirical analysis of regular consumption behavior, a key step is to determine the thresholds (dash lines in Figure SM 7) under and above which a consumer can be categorize as conventional or quality regular, respectively. To do so, for each product's organic distribution, we fit a beta distribution, the only statistically function with a known density and cumulative distribution function that can easily account for bimodality. Using the quantile function of the fitted beta distribution, we assess the values of each pair of centiles which a 0.1 (10%) difference. In this sense, we evaluate two values, between which only 10% of the theoretical beta distribution lies. To assure that these two values are symmetrically delimiting the two regular behaviors (conventional and quality regularity): noting $threshold_1$ the threshold for the conventional regularity, and $threshold_2$ for the organic regularity, we set the constraint as $threshold1_1 = 1 - threshold_2$.

Figure SM 7. Density and quantile function of the Beta function



We compute theses thresholds values for 5 key products and use 20% and 80% of quality consumption as the thresholds of conventional regularity and quality regularity respectively (Table SM 9).

Table SM 9. Estimated thresholds of conventional and quality regularities

Product	Threshold conventional regularity	Threshold quality regularity
Milk	0.14	0.86
Egg	0.21	0.79
Oil	0.24	0.76
Lemon	0.20	0.80
Baby Food	0.17	0.83

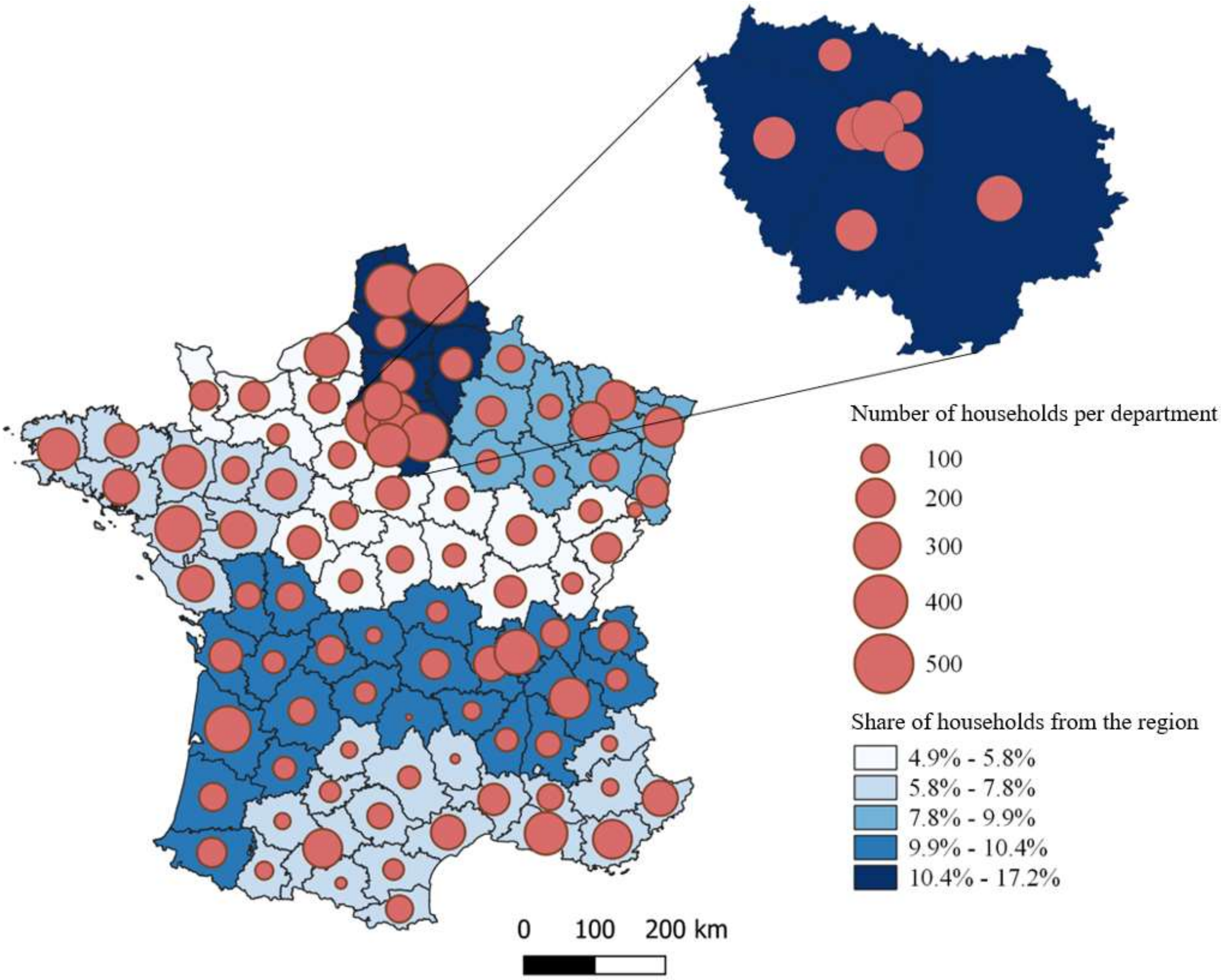
SM 2. Identification of the variables influencing availability

To construct the indicator of organic products' availability, we collected data on which organic products were available in 10 shops of each of the 5 biggest supermarket brands in France in a region (Burgundy) based on their websites. The shops are of different sizes (supermarkets, hypermarkets), are located in 4 different "départements" and in different city sizes. However, they all offer the possibility to purchase food online and pick it up at the shop ("Drive in"). We then run LASSO regression using the number of organic products available in each shop as the dependent variables. We find that supermarkets' brands and size are the only variables that influence the availability of organic products once penalized. When all the variables are included, an ordinary least squares regression explains 86% of the variance of the number of organic products available and when only the supermarkets' brands and size are selected, the R^2 still amounts to 68%.

Table SM 10. LASSO regression results on the availibility of organic products

Variables	Penalized coefficients
Département1	0.00
Département2	0.00
Département3	0.00
Brand1	449.9
Brand2	-201.2
Brand3	0.00
Brand4	0.00
City Inhabitants : 20k-50k	0.00
City Inhabitants : 50k-100k	0.00
City Inhabitants : 5k-10k	0.00
City Inhabitants : 10k-20k	0.00
City Inhabitants : Smaller than 2k	0.00
City Inhabitants : 2k-5k	0.00
Shop Size : Small	-66.6

SM 3. Map of the spatial distribution of the sample



SM 4. Detailed results of the logit

	Full Logit	Full Logit Household	Full Logit Products	Restricted Logit	Restricted Logit Household	Restricted Logit Products
	(1)	(2)	(3)	(1)	(2)	(3)
Year 2012	0.119***	0.167***	0.116***	0.085*	0.097**	0.080*
	(0.042)	(0.040)	(0.042)	(0.044)	(0.042)	(0.044)
Year 2013	0.233***	0.299***	0.225***	0.117***	0.146***	0.107**
	(0.041)	(0.039)	(0.041)	(0.044)	(0.042)	(0.044)
Year 2014	0.281***	0.350***	0.276***	0.188***	0.220***	0.179***
	(0.041)	(0.038)	(0.040)	(0.043)	(0.041)	(0.043)
Year 2015	0.360***	0.425***	0.354***	0.193***	0.235***	0.184***
	(0.041)	(0.039)	(0.041)	(0.043)	(0.041)	(0.043)
Year 2016	0.450***	0.585***	0.440***	0.197***	0.274***	0.186***
	(0.040)	(0.038)	(0.040)	(0.043)	(0.040)	(0.042)
Number of purchases	-0.248*** (0.019)	-0.250*** (0.016)	-0.247*** (0.019)	-0.008*** (0.001)	-0.009*** (0.001)	-0.008*** (0.001)
Hard-discount	0.453***		0.427***	-0.097		-0.104
	(0.063)		(0.063)	(0.064)		(0.064)
Home delivery	0.323***		0.336***	0.012		0.017
	(0.119)		(0.118)	(0.123)		(0.123)
HyperMarket	0.557***		0.548***	0.197***		0.203***
	(0.044)		(0.044)	(0.046)		(0.046)
Organic Shop	3.360***		3.357***	1.809***		1.813***
	(0.052)		(0.052)	(0.051)		(0.051)
Small Supermarket	0.507***		0.501***	0.201***		0.198***
	(0.060)		(0.060)	(0.063)		(0.063)
SuperMarket	0.527***		0.522***	0.218***		0.216***
	(0.040)		(0.040)	(0.042)		(0.042)
Retailer brand	0.817*** (0.024)		0.815*** (0.024)	0.704*** (0.027)		0.705*** (0.027)
Price ratio between organic & conventional	0.018 (0.015)		0.017 (0.015)	0.181*** (0.033)		0.182*** (0.033)
Average share of organic purchases	0.540*** (0.008)	0.525*** (0.005)	0.539*** (0.008)	0.054*** (0.003)	0.033*** (0.002)	0.053*** (0.003)
Number of times purchased	-0.647***	-0.215***	-0.648***	-0.000***	-0.000***	-0.000***
	(0.015)	(0.009)	(0.015)	(0.000)	(0.000)	(0.000)
Youngest child <25 month	0.065 (0.078)	0.232*** (0.076)		0.030 (0.074)	0.094 (0.072)	
Youngest child >25 months and <5 years	-0.062 (0.075)	0.035 (0.074)		-0.028 (0.070)	0.014 (0.069)	
Youngest child >6 years and <10 years	-0.077 (0.074)	-0.053 (0.072)		0.000 (0.069)	0.012 (0.068)	
Youngest child >11 years and <15 years	-0.072 (0.071)	-0.128* (0.069)		0.015 (0.070)	-0.022 (0.068)	
Farmers	-0.648*	-0.604*		-0.343	-0.386	
	(0.346)	(0.355)		(0.302)	(0.299)	
Managers and superior professions	0.325*** (0.086)	0.315*** (0.085)		0.153** (0.074)	0.205*** (0.073)	
Employees	-0.063	-0.012		0.034	0.027	
	(0.069)	(0.068)		(0.060)	(0.060)	
Manual occupations	-0.326***	-0.267***		0.035	-0.052	
	(0.077)	(0.077)		(0.069)	(0.068)	

Intermediate professions	0.039	0.105		0.107*	0.145**	
	(0.074)	(0.075)		(0.064)	(0.064)	
Retired	-0.241	-0.223		-0.246	-0.203	
	(0.192)	(0.195)		(0.166)	(0.168)	
Unemployed, student	-0.215	-0.159		-0.083	-0.064	
	(0.192)	(0.186)		(0.170)	(0.167)	
City of 2000-4999 inhabitants	0.151	0.192*		-0.048	0.012	
	(0.112)	(0.113)		(0.093)	(0.094)	
City of 5000-9999 inhabitants	0.081	0.113		-0.012	0.012	
	(0.119)	(0.121)		(0.099)	(0.099)	
City of 10 000-19 999 inhabitants	0.284**	0.334***		0.110	0.181*	
	(0.121)	(0.121)		(0.098)	(0.098)	
City of 20 000-49 999 inhabitants	0.230**	0.238**		0.130	0.193**	
	(0.116)	(0.117)		(0.093)	(0.093)	
City of 50 000-99 999 inhabitants	0.036	0.060		0.013	0.053	
	(0.115)	(0.116)		(0.094)	(0.094)	
City of 100 000-199 999 inhabitants	0.339**	0.356***		0.068	0.180*	
	(0.134)	(0.137)		(0.106)	(0.107)	
City of more than 200 000 inhabitants	0.330***	0.335***		0.066	0.158**	
	(0.078)	(0.079)		(0.063)	(0.064)	
Paris agglomeration	0.191**	0.180**		-0.066	0.065	
	(0.088)	(0.089)		(0.071)	(0.070)	
Single	-0.170***	-0.109**		-0.100**	-0.130***	
	(0.053)	(0.051)		(0.050)	(0.049)	
High income household	0.109**	0.090*		-0.052	-0.027	
	(0.050)	(0.049)		(0.044)	(0.044)	
Inferior middle income household	-0.140*	-0.115		-0.031	-0.021	
	(0.085)	(0.085)		(0.075)	(0.074)	
Low income household	-0.206	-0.192		-0.163	-0.136	
	(0.170)	(0.173)		(0.148)	(0.149)	
BMI	-0.198***	-0.216***		-0.020***	-0.031***	
	(0.028)	(0.028)		(0.006)	(0.006)	
Absolute price difference	0.031*		0.031*	-0.101		-0.101
	(0.016)		(0.016)	(0.079)		(0.079)
Availibility	0.335***		0.340***	0.574***		0.576***
	(0.016)		(0.016)	(0.069)		(0.069)
Alcoholic beverages	-0.628**		-0.629**	-0.233		-0.236
	(0.273)		(0.273)	(0.293)		(0.294)
Appetizers	-0.615**		-0.613**	-0.281		-0.283
	(0.240)		(0.240)	(0.258)		(0.259)
Baby foods	0.884***		0.911***	0.610**		0.634**
	(0.266)		(0.266)	(0.287)		(0.286)
Biscuits, cakes and pastry	0.592**		0.591**	0.612**		0.614**
	(0.255)		(0.255)	(0.274)		(0.275)
Bread, flour	0.826***		0.826***	0.547**		0.547**
	(0.255)		(0.255)	(0.274)		(0.274)
Cheese	-0.138		-0.140	-0.069		-0.076
	(0.268)		(0.268)	(0.289)		(0.289)
Confectionary products	0.618**		0.617**	0.677**		0.677**
	(0.257)		(0.257)	(0.277)		(0.277)
Culinary ingredients	0.184		0.184	0.486*		0.486*
	(0.253)		(0.253)	(0.273)		(0.273)
Desserts	0.674***		0.672***	0.615**		0.615**
	(0.257)		(0.258)	(0.277)		(0.277)
Eggs	2.283***		2.284***	1.992***		1.998***
	(0.052)		(0.052)	(0.058)		(0.058)

Fat	1.078***		1.077***	0.941***		0.941***
	(0.253)		(0.253)	(0.272)		(0.272)
Hot drinks	2.345***		2.325***	15.389		15.302
	(0.545)		(0.545)	(105.970)		(106.791)
Meal	0.670***		0.669***	0.931***		0.933***
	(0.256)		(0.256)	(0.276)		(0.277)
Meal subsitutes	0.165		0.163	1.712***		1.705***
	(0.411)		(0.411)	(0.589)		(0.588)
Meat	0.101		0.103	0.198		0.202
	(0.128)		(0.128)	(0.129)		(0.129)
Milk	2.496***		2.496***	2.321***		2.327***
	(0.053)		(0.053)	(0.060)		(0.060)
Non Alcoholic beverages	0.648**		0.645**	0.573**		0.571**
	(0.259)		(0.259)	(0.279)		(0.279)
Processed F&V	0.159		0.161	0.381		0.380
	(0.256)		(0.256)	(0.277)		(0.277)
Processed Meat	0.164		0.167	0.372		0.366
	(0.259)		(0.259)	(0.280)		(0.280)
Seafood	-0.837***		-0.834***	-0.358		-0.376
	(0.282)		(0.282)	(0.328)		(0.328)
Starchy foods	0.283		0.283	0.186		0.186
	(0.256)		(0.256)	(0.275)		(0.276)
Sweeteners	0.491		0.162	0.474		0.228
	(0.621)		(0.259)	(0.578)		(0.303)
Processed Product	0.318		0.317	0.257		0.260
	(0.250)		(0.250)	(0.269)		(0.269)
Constant	-8.406***	-6.662***	-8.319***	-2.567***	-0.972***	-3.059***
	(0.090)	(0.077)	(0.061)	(0.178)	(0.161)	(0.089)
Number of households	12453	12453	12453	8854	8854	8854
Household random effect standard deviation	2.162	2.222	2.228	1.162	1.174	1.207
Observations	1,221,430	1,221,430	1,221,430	70,549	70,549	70,549
Log Likelihood	-47,361.98	-53,322.82	-47,492.58	-31,058.4	-33,801.1	-31,084.5
Akaike Inf. Crit.	94,857.95	106,713.6	95,071.16	62,250.99	67,670.07	62,254.9

Notes:

***, **, *, Significant at the 1, 5, 10 percent levels respectively. The values between brackets refer to the standard deviation of the coefficients.

Retailer brand is a dummy that takes the value 1 if more than 50% of the purchases of a product where from the retailer brand.

A household of 4 members is considered of low income if its monthly income in under 2094€ and of high income if its monthly income is above 5808€.

Dummy variables	Reference level
Shop type	Open-air market
Youngest child	No children
Working occupation	Artisan and craftsman
Size of City	<500 inhabitants
Economic status	Superior middle income
Product family	Fresh F&V

Chapter 4

Price elasticity of organic and conventional food in France: a censored EASI demand system.

Note: This chapter is based on work-in-progress at the time of this thesis' redaction. The results from this chapter are not definitive, please do not cite them.

4.0. Abstract

From 2011 to 2018, the French organic market has increased by 149%, accounting eventually for almost 5% of French households' food expenditures. Such an increase might have various drivers: a change in the relative price of organic products compared to conventional ones, a wider availability of organic products, an increase in households' food expenditures or some life cycle changes (marriage, urbanisation, new-borns, retirement…) that affect preferences toward organic food.

Using scanner data and a censored EASI demand system, we estimate price and expenditures elasticities of organic and conventional food in France from 2011 to 2018. We find that own-price elasticities of organic products are considerably larger than conventional products and that organic products are mostly luxury goods (expenditures elasticities are more than unity). Moreover, organic products are complements among themselves (negative cross-price elasticities) and substitutes of conventional products (positive cross-price elasticities). Organic food demand is thus reactive to price changes and an exemption of VAT for organic products would increase their market share by 40%.

Keywords: *organic food; EASI demand system; price elasticities; demographic variables.*

4.1. Introduction

From 2011 to 2018, the French organic market has increased by 149%, rising from €3.9 billion to 9.7€ billion, accounting eventually for almost 5% of French households' food expenditures (Figure SM 1.a., Agence Bio, 2019a). This increase of organic food consumption is mostly homogenous across product families and the composition of the organic market has not changed a lot between 2011 and 2018: fruits and vegetables account for 15% of the organic market, dairy product for 10%, processed products for 20% and meat for 8% (Figure SM 1.b). Moreover, for all families of products, the share of organic products (relatively to the share of conventional products) is steadily increasing (Figure SM 1.c). In addition, organic food production and consumption has also taken a key place in public policies (Egalim law in France, Farm to Fork in the European Union) as a way to promote healthier diet as well as mitigating climate change due to the lower pesticide and fertilizer uses.

Concomitantly, organic food consumption is being increasing scrutinized in academic research, especially in economics, marketing and sociology. Indeed, consumption behavior can be studied from a large spectrum of scientific disciplines which have provided extensive knowledge on the factors that influence organic food purchases and consumption. Such factors include prices, expenditures and socio-demographics characteristics as well as non-economic motivations such as personal health, environmental impacts, labor ethics or animal welfare (Gracia and de Magistris, 2008; Padilla Bravo et al., 2013).

More precisely, regular organic consumers have a higher education and income than households purchasing mainly conventional products (Lambotte et al., 2020; Ngobo, 2011). Organic consumers are also more often female and have children, especially young ones (Hughner et al., 2007). They spend slightly more money on food and have a healthier diet (Boizot-Szantai et al., 2017; Kesse-Guyot et al., 2013). Heavy organic consumers' diets also result in lower greenhouse gases emissions, land occupation due to a lower consumption of animal products (Baudry et al., 2019; Seconda et al., 2018). Logically, organic consumers value more credence attributes than search and experience attributes (Massey et al., 2018; Rana and Paul, 2017), which explains that the influence of credence attributes such as animal welfare, GMO-free , eco-packaging, fair trade or environmental friendliness on the probability of purchasing organic products has been found to be larger than that of education, marital status, and income (Padilla Bravo et al., 2013).

Here we focus on the price driver and quantify the price-elasticities of organic products. These estimates are particularly important in a context where European policy makers are looking for instruments to reach the Green deal target of 25% organic area in 2030. In particular, we estimate how much rise in organic consumption can be expected from a VAT exemption for organic products and other fiscal measures, as well as how the effect of these measures differs across product categories.

More precisely, we propose the following hypothesis concerning cross-prices elasticities:

- H_1: Within a given quality (conventional or organic), products have negative cross-price elasticities, i.e. organic products are complements with one another.
- H_2: The cross-price elasticities of conventional products in regard to their organic counterparts are small as the fact that a consumer shifts from conventional to organic food is not mainly determined by price factors.
- H_3: The cross-price elasticities of organic products in regard to their conventional counterparts are large, as consumers that are already purchasing organic products would reactively increase their consumption of organic food when conventional food prices increase (and vice-versa).

The literature shows inconclusive evidence with respect to the role of price in organic consumption behavior as the effects of price strongly differ between product categories and retail stores (Buder et al., 2014; Dimitri and Dettmann, 2012; Padel and Foster, 2005; Rödiger and Hamm, 2015). In the same review, Rödiger and Hamm (2015) also show that consumers were generally willing to pay a higher price for organic products. However, they insist on the fact that willingness to pay (WTP) differs greatly depending on the product categories and consumer segments. Finally, they reveal that WTP is positively influenced by the consumers' attitudes toward organic food.

One reason for the inconclusiveness of most studies concerning the role of price in organic consumption behavior relates to the small sample size of surveys and the intension-behavior gap, the bias between what interviewed consumers declare when surveyed and what they actually purchase and consume (Chekima et al., 2017; Zhen et al., 2019). To address these limits a growing field of the literature has used large panel data of actual purchases of thousands of household - such as Kantar's Wordpanel® or Nielsen's Homescan® to model demand systems and estimate price elasticities. In France, scanner panel data has been used to study organic consumption (Boizot-Szantai et al., 2017; Monier et al., 2009) or to estimate price elasticities of conventional food (Allais et al., 2010; Caillavet et al., 2016) but price elasticities for organic products have not yet been estimated yet. In addition, most studies worldwide focus on a specific product - often milk (Alviola and Capps, 2010; Bernard and Bernard, 2009; Glaser et al., 2000; Jonas and Roosen, 2008; Lopez and Lopez, 2009; Schröck, 2012) - or products' family - fruits and vegetables mostly (Bunte et al., 2007; Fourmouzi et al., 2012; Kasteridis and Yen, 2012; Lin et al., 2009; Zhang et al., 2011). To our knowledge, an exhaustive demand system for all organic food has not yet been proposed. Moreover, an estimation of price elasticities for both organic and conventional food allows the investigation of asymmetric price responses. Asymmetric price elasticities for organic food, such as enounced in H_2 and $H_{3,}$ has been recognized by previous research for specific products: Glaser et al. (1999) for frozen vegetables, Zhang et al. (2011) for fresh ones, Glaser et al. (2000) and Alviola and Capps (2010) for milk, but has never been studied for all products. Asymmetries in price responses of organic and conventional food are key to understand consumer behavior, as they give precious information on the transitions and substitutions between conventional and organic products. Indeed, heavy organic consumers may not respond to conventional price changes as price is not a key determinant of their consumption of organic food, but conventional consumers could respond strongly to a decrease of organic food prices.

In addition to the issue of data availability, a technical difficulty may explain the scaricity of price-elasticity estimates in the literature. Indeed, 70% of consumers never purchase organic products and thus spend 0% of their budget on organic food (Lambotte et al., 2020) and this high share of zero purchases for organic products necessitates the estimation of a censored demand system, a tool which is not directly available in existing statistical packages.

In short, we propose the estimation of a censored demand system for both organic and conventional food from 2011 to 2018 in France to deepen the understanding of how prices drive organic food consumption. We thus estimate own and cross price elasticities, expenditures elasticities and incorporate in these estimates the influence of the availability of organic products and the socio-demographic characteristics of consumers. We show that a subvention, resulting in a 20% price reduction of organic food is unlikely to be sufficient to reach the Green deal target (25% of organic land in the EU, translated here in a market share of 25% for organic food) and that it is most effective on food categories which are highly sensible to price variation (Fruits & Vegetables, animal products).

4.2. Data

We use the Kantar Worldpanel® scanner data in France from 2011 to 2018, which can be treated as an unbalanced panel data of food purchases from a sample of roughly 12,000 French households per year. The households participate in the data collection during 5 years on average, and this dataset can thus be assimilated to an unbalanced panel data. This panel data contains socio-demographic information about the households and detailed information about the food products they purchase: the price paid and the quantity purchased, brand, size and type of shops and more crucially in our case, whether the products are organic. The different items purchased are categorized into 334 products, which are then grouped into 7 products' families (see SM 2 for details): animal products, dairy products, cooking ingredients, starchy food, fruits and vegetables, drinks, and lastly processed food. These 7 products families are distinguished in both organic and conventional qualities, yielding 14 different product families in our final analysis. Prices and quantities are aggregated per quarter.

In addition, we compute an indicator of the availability of organic products defined in Lambotte et al. (2020). The indicator is defined as the share of shops which offer the organic product of interest out of all shops where the household is shopping. More precisely, an organic product is available in a given shop for a given household if it has been purchased by others households of our sample in a shop from the same retail chain, of the same size (hypermarket vs. supermarket) and in the same administrative region.

4.3. Methodology

4.3.1. Demand system as framework for analysing the drivers of the increase of organic food consumption

Our econometric model is based on the Exact Affine Stone Index demand system, which is highly flexible in estimating expenditures elasticities and allows for the inclusion of socio-demographic variables and other demand shifters in the budget shares' equations (details are given in subparts 4.3.2 to 4.3.4.).

To address price endogeneity (simultaneity between price and demand) and unit value bias, we use Fisher Ideal price indices as instrumental variables in which missing prices are based on the average prices faced by the households who shop in the same administrative region and supermarket brand (details are available in subpart 4.3.5.).

The high frequency of zero purchases, in particular for organic products, is handled with the Shonkwiler and Yen (SY) two-step estimation for censored system of equations (Shonkwiler and Yen, 1999, more information is available in 4.3.6.).

4.3.2. The Exact Affine Stone Index demand system specification

More specifically, we draw from the EASI (Exact Affine Stone Index) incomplete demand system for censored data introduced by Cardwell et al. (2015) and Castellón et al. (2015), based itself on the original EASI model of Lewbel and Pendakur (2009). As we only have information on the households' food expenditures, we cannot estimate a complete demand system, which require information on the households' real income (LaFrance, 1990). Thus, we estimate a conditional demand system, i.e. the results hold conditional on the expenditures for the groups of food products and non-food goods. However, assuming that the expenditures on food products are weakly separable to non-food commodities (energy, transport, housing, clothes...) is a common and reasonable assumption. Moreover, as we are not estimating welfare changes, we are not strongly concerned by the endogeneity of group expenditures, which in reality creates a small bias in the EASI framework (Lewbel and Pendakur, 2009). The conditional EASI demand system can be written in its most disaggregated form as:

$$w_{hit} = \sum_{j=1}^{J} a_{ij}\, lnp_{hjt} + \sum_{r=1}^{L} b_{ir} y_{ht}^{r} + \sum_{k=1}^{K} g_{ik}\, z_{hkt} + \mu_{hit},\ \ h = 1, \dots, H;\ i = 1, \dots, J;\ t = 1, \dots, T \qquad (1)$$

where w_{hit} is the budget share of the i^{th} product category for the h^{th} household at time t, p_{hjt} is the price index, J is the total number of product families, y_{ht} is the log of the household's real food expenditures,

L is the highest order of polynomial of y_{ht} that should be determined empirically, K is the number of exogenous demand shifters (socio-demographic variables, time trend and availability index) that influence preferences, z_{hkt} is the k^{th} demand shifters, with $z_{h1t} = 1$, i.e. g_{i1} is the intercept in the budget share equations. a_{ij}, b_{ir} and g_{ik} are parameters to be estimated and μ_{hit} are the residuals which here directly account for unobserved preferences heterogeneity as random utility parameters (Lewbel and Pendakur, 2009). To assure that the model is consistent with economic theory and the utility maximization framework, the following restrictions are imposed during the estimation (adding-up, homogeneity, symmetry):

$$\sum_{i=1}^{J} b_{i0} = 1,\ \sum_{i=1}^{J} b_{ir} = 0\ ,\sum_{i=1}^{J} a_{ij} = \sum_{i=1}^{J} g_{ik} = \sum_{i=1}^{J} \mu_{hit} = 0,\ a_{ij} = a_{ji}. \quad (2)$$

y_{ht}, the log of the household's real food expenditures, is expressed as an affine transformation of the log nominal of food expenditures x_{ht} deflated by the Stone index, hence the name of the model (Pendakur, 2009):

$$y_{ht} = \ lnx_{ht} - \sum_{j=1}^{J} w_{hjt} lnp_{hjt} + \frac{1}{2}\sum_{j=1}^{J}\sum_{i=1}^{J} a_{ij} lnp_{hjt} lnp_{hit}. \quad (3)$$

With such an exact definition of y_{ht}, equation (1) can be written as:

$$w_{hit} = \ \sum_{r=1}^{L} b_{ir}(lnx_{ht} - \sum_{j=1}^{J} w_{hjt} lnp_{hjt} + \frac{1}{2}\sum_{j=1}^{J}\sum_{i=1}^{J} a_{ij} lnp_{hjt} lnp_{hit})^{r} + \sum_{i=1}^{J} a_{ij}\ lnp_{hjt} + \sum_{k=1}^{K} g_{ik}\ z_{hkt} + \mu_{hit} \quad (4)$$

which is non-linear, because the coefficient b_{ir} multiplies a_{ij} power *r*, and endogenous, as the budget share w_{iht} appears in both side of the equation. However, Lewbel and Pendakur (2009) have shown that the non-linearity can easily be dealt with by using an approximate EASI model, which defined $\tilde{y}_{ht}$ as the log of the Stone-index deflated nominal expenditures, an approximation to the real household's expenditures y_{ht}:

$$\tilde{y}_{ht} = lnx_{ht} - \sum_{j=1}^{J} w_{hjt} lnp_{hjt}. \quad (5)$$

The estimators obtained with the approximate EASI model are numerically very close to the real ones, and using the approximate expression has been the common practice as it releases a lot of the computational burden of the estimation (Lewbel and Pendakur, 2009; Zhen et al., 2014). The endogeneity of the budget shares can be dealt with in using $\overline{w}_{jt}$, the sample average budget share, instead of w_{hjt} in equation (4), yielding $\bar{y}_{ht} = lnx_{ht} - \sum_{j=1}^{J} \overline{w}_{hjt} lnp_{hjt}$. However, this specification has been shown to leave *y* unchanged ($\tilde{y}_{ht}$ and $\bar{y}_{ht}$ have a correlation of 0.998 in the data used by (Lewbel and Pendakur, 2009)) and is therefore rarely implemented.

4.3.3. Inclusion of socio-demographic variables and other demand shifters

The possibility to include socio-demographic variables in the EASI model is of particular importance to our analysis. Indeed, this method of inclusion of demand shifters, related to the concept of demographic translation introduced by (Pollak and Wales, 1981), modifies both the intercepts and the regression parameters of prices and expenditures (from which elasticities are computed) but still allow the aggregation of the households ($w_{it} = \frac{\sum_{h=1}^{H} x_{ht} wh_{it}}{\sum_{h=1}^{H} x_{ht}}$, (Muellbauer, 1974)) to accommodate the estimation of population-valid elasticities.

4.3.4. Flexibility of the expenditures elasticities and non-linear Engel curves

The high flexibility of the EASI model, especially in the large order of polynomials (in this study, three) of y_{ht} it accommodates, allows the estimation of non-linear Engel curves and an in-depth study of the expenditures elasticities of organic products. Indeed, as expenditures is different across households, and as expenditures elasticities also vary among products, a high variety of relationships between expenditures and products are expected, which cannot be correctly estimated with linear Engel curves (Banks et al., 1997).

4.3.5. Correcting for the endogeneity of prices in the EASI demand system

Sources of price endogeneity in scanner data

Demand systems estimated with scanner data suffer from endogeneity in the disaggregated prices, which might be due to any of the common econometric reasons: omitted variables, measurement errors and simultaneity.

- Simultaneity of supply and demand in the formation of price is not an issue in disaggregated demand systems as the households are rather atomistic and do not have the market power to influence market equilibrium prices (Zhen et al., 2014).
- Omitted variables and measurements errors are likely to occur in disaggregated demand systems as the households' preferences and the prices are not averaged. The main source of endogeneity in scanner data originates from the fact that the information on prices is based on unit values, i.e. for a given food category, the mean of the prices paid by a consumer for products in this category, divided by the quantities purchased (Boonsaeng et al., 2019). Thus, the unit values integrate both an exogenous price and a quality-related price, the households who value quality more have higher unit values than the households who do not. This quality-related price leads to the so-called unit value bias, as a change in the unit value of a given category for a given

household integrates both the exogenous change of the true prices and the endogenous change of quality as the household might modify the mix of quality-differentiated products in his purchase basket when the prices change. For example, if real prices increase, households might react by lowering the quality of the products purchased, and the unit value will increase less than the real prices increase. Thus, in the demand equation, the same change in the budget share will be associated to a lower change in unit values, yielding upper-biased regression coefficients for the unit values, compared to an estimation with the true prices (which vary more and thus have a lower regression coefficient (Deaton, 1988)). Similarly, if the regression coefficients obtained with unit values are used to predict the impacts of real price changes on demand, these impacts will be overestimated.

Finally, omitted variables, such as the true households' preferences, may create endogeneity in prices. Indeed, the households who have a strong preference for some food products and purchase a high quantity of them are more likely to spend some time or resources to find lower prices as these products weight more on their expenditures, and so they are abler to purchase them at a lower prices: p_{hit} for such households will be lower than for other households.

- Unit values are also subject to important measurement errors, especially compared to real prices or prices gathered at shops, which leads to attenuation bias, biasing the prices coefficients toward zero. The purchased quantities, used to construct unit values, can also be mismeasured, especially in the case of fresh fruits and vegetables. The measurement errors are reflected in both the left and right sides of the budget share equation (the measure of quantities intervenes in the computation of both the budget shares and the unit values), the quantities and unit values are negatively correlated and the quantities and budget share are positively correlated. Thus, if the quantities are mismeasured, for example overestimated, the budget shares will also be overestimated, but the unit values will be underestimated. The relation between budget shares and unit values, of keen interest in a demand system, is afflicted by the negative correlation between the quantity and unit values and the estimated relation will be more negative than the true relation without measurement errors (Olivia and Gibson, 2003).

Price indexes and endogeneity correction

In our discussion of the differences between complete and incomplete demand system, we have underlined that expenditures endogeneity is negligible in the EASI based demand systems. However, price endogeneity leads to important misspecifications of the demand systems as Zhen et al. (2014) show using Nielsen®'s Homescan panel data. Thus, we implement instrument variables for the prices in the SY procedure for censored demand systems and we compute the Fisher Ideal (FI) price index of each food category, for each household and at each time period (here quarters) to correct for unit values bias.

The FI index is the geometric mean of the Laspeyre and Paasches indices and is viewed as ideal and superlative as it provides a second-order differential approximation to any twice differential cost function (Boonsaeng et al., 2019; Diewert, 1998). More precisely, the Laspeyres index computes the price differential between how much a given household pays for an average quantity of a given products' family (aggregating *k* products) relative to the average household; while the Paasche index estimates the price ratio between how much a given household pays for its own consumption of a products' family relative to the price the average household would pay for the same quantity.

Doing so, we mitigate any potential bias related to the use of unit values by weighting individual unit values and quantity purchases of disaggregated goods by national averages (variables indexed with 0 in equation (6)) when aggregating these unit values to compute the aggregated products' families FI indices. More importantly, using the FI index eases the comparison between price and budget shares of the conventional and organic version of a same products' family as the aggregation procedure in the FI index computation account for the quantities of each product.

The FI price index for a given product's family, household and time is computed as follow:

$$p_{hit} = \sqrt{\frac{\sum_k p_{hkt} q_{k0} \sum_k p_{hkt} q_{hkt}}{\sum_k p_{k0} q_{k0} \sum_k p_{k0} q_{hkt}}}, \tag{6}$$

where p_{kht} and q_{kht} are the price and quantity purchased of the food product *k* by household *h* at time *t* respectively and p_{k0} and q_{k0} are the base price and quantity of product *k*, computed as the average national price and quantity of *k* in the first quarter of 2011. If the household *h* does not purchase any good from the category *i* at time *t*, then $\sum p_{k0}\, q_{hkt}$ and $\sum p_{kht} q_{hkt}$ equals zero, i.e. the demand is censored. Moreover, when the household *h* does not purchase the good *k* in time *t*, we do not have information on p_{hkt} and we estimate the missing prices as the average price of the good *k* from all the households who purchased this good in time *t*, shopping in a shop from the same brand and size as the household *h* and living in the same region (for organic products, which are less purchased, we only considered household shopping in a shop of the same brand). More precisely, we create clusters of households, based on the time period, the brand and size of shops they purchased from and the region they live in, in a similar fashion as Zhen et al. (2019). So, in the case of missing price from a household who does not purchase a given good *k*, we use the average price of the cluster the household belongs to, p_{gkt}, where $g = 1, \dots, G$ indicates the cluster, G being the total number of cluster (shops' brand x region x shops' size = 11 x 14 x 2 = 308 clusters), which maintains an important price variability between each cluster (Ferrier et al., 2017). Thus, when constructing the FI price index for a given household, we replace $\frac{\sum p_{kht} q_{kht}}{\sum p_{k0} q_{kht}}$ by $\frac{\sum p_{kgt}}{\sum p_{k0}}$ for the *k* goods the household did not purchase at time t.

This methodology is also akin to the one developed by Muth et al., (2020), except that we do not have information on the official retail prices for each good *k* as they do, so we estimate them as the average of all purchases of *k* from a cluster of households.

Similarly, we compute the clustered FI price indexes for a category i, p_{git}, using only the average p_{gkt} that were computed in the previous step to estimate the missing prices in the households' specific FI price indexes. The clustered FI price indexes for a category are used as instruments for individual price indexes p_{hit} in the estimation of the demand system in order to eliminate prices endogeneity as the clustered FI price indexes are an average of households' prices indexes in a given cluster, where households face similar prices, limiting the possibility of simultaneity, omitted variables and measurement errors from unit values (Muth et al., 2020; Zhen et al., 2014). This instrumentation of individual price indexes is directly related to the cluster approach of Deaton (1988). To keep consistency with the availability index we developed, we clustered the households on the same criteria: region, size and brand of shops visited.

4.3.6. Accounting for the censoring of budget shares

Scanner data, with its rich information on households and purchasing patterns, in conjunction with the high flexibility of the EASI demand system, are powerful tools to analyse the demand for organic products.

Table 1. Percentage of censored (zero) observation per product families

	Conventional	Organic
Animal	0.1%	75.3%
Dairy	0.6%	83.2%
Drinks	0.2%	71.7%
FV	0.3%	58.4%
Ingredients	0.1%	63.8%
Processed	0.1%	74.8%
Starchy	1.7%	66.0%

However, demand systems based on scanner data suffer from the presence of many zero-purchases, especially for some categories of organic products (Table 1), and the budget shares are censored (Heien and Wessells, 1990; Muth et al., 2020; Zhen et al., 2014). Indeed, the budget shares are designed to lie between 0 and 1 and thus cannot be negative. The budget shares that are null can be seen as censored by an unobservable variable controlling the decision to purchase or not products among the considered categories. To correctly estimate the parameters in such a censored system of equations, we apply the two-step procedure of Shonkwiler and Yen (1999).

Consider the following system of equations representing the censoring of the budget shares w_{hit}:

$$w_{hit}^{*} = f\left(Z_{hkt}, p_{hjt}, y_{ht}; \theta_i\right) + \mu_{hit} \tag{7}$$

where $f(.)$ corresponds to the specification given in equation (1) and θ_i is the vector of parameters,

$$w_{hit} = d_{hit} w_{hit}^{*} \tag{8}$$

where w_{hit} is the observed budget share, w_{hit}^{*} is the latent budget share and d_{hit} is a dummy variable defining the selection process (if household h purchased the products' family i at least one at time t, $d_{hit} = 1$, and zero otherwise):

$$d_{hit} = \begin{cases} 1 if\ d_{hit}^{*} > 0 \\ 0\ if\ d_{hit}^{*} \leq 0' \end{cases} \tag{9}$$

where $d_{hit}^{*} = s'_{hit}\rho_i + \varepsilon_{hit}$, (10)

and the latent dependent variable d_{hit}^{*} is estimated by a matrix of socio-demographic variables and an availability indicator s_{hit}.

The two step procedure then consists of the maximum likelihood probit estimations of equation (10) for all products' families, to obtain the estimates $\widehat{\rho_i}$ of the selection parameters ρ_i and then calculate the cumulative distribution function (cdf) $\widehat{\Phi}_{hit}(s'_{hit}\rho_i)$ and the probability density function (pdf) $\hat{\phi}_{hit}(s'_{hit}\rho_i)$.

In the second step, the EASI system of equation defined in (1) is augmented with the $\widehat{\Phi}_{hit}(s'_{hit}\rho_i)$ and $\hat{\phi}_{hit}(s'_{hit}\rho_i)$:

$$w_{hit} = \widehat{\Phi}_{hit}\left(\sum_{i=1}^{J} a_{ij}\, lnp_{hjt} + \sum_{r=1}^{L} b_{ir} y_{ht}^{r} + \sum_{k=1}^{K} g_{ik}\, z_{hkt}\right) + \delta\hat{\phi}_{hit} + \varepsilon_{hit} \tag{11}$$

Equation (11) is estimated using 3SLS as we introduce instrument variables for y_{ht}^{r} and because the budget shares of a same household are correlated. However, the adding-up restrictions only holds for the latent equations (7). To address this issue, the $n-1$ products' family (here organic starchy food) is treated as a residual category and the system in (11) is estimated for $i = 1,2,\dots,n-1$ (Drichoutis et al., 2008; Yen et al., 2003). As shown in the footnote 9 of Yen et al. (2003), the Marshallian, Hicksian and expenditures elasticities for the n^{th} products' family can be retrieved using the budget constraint.

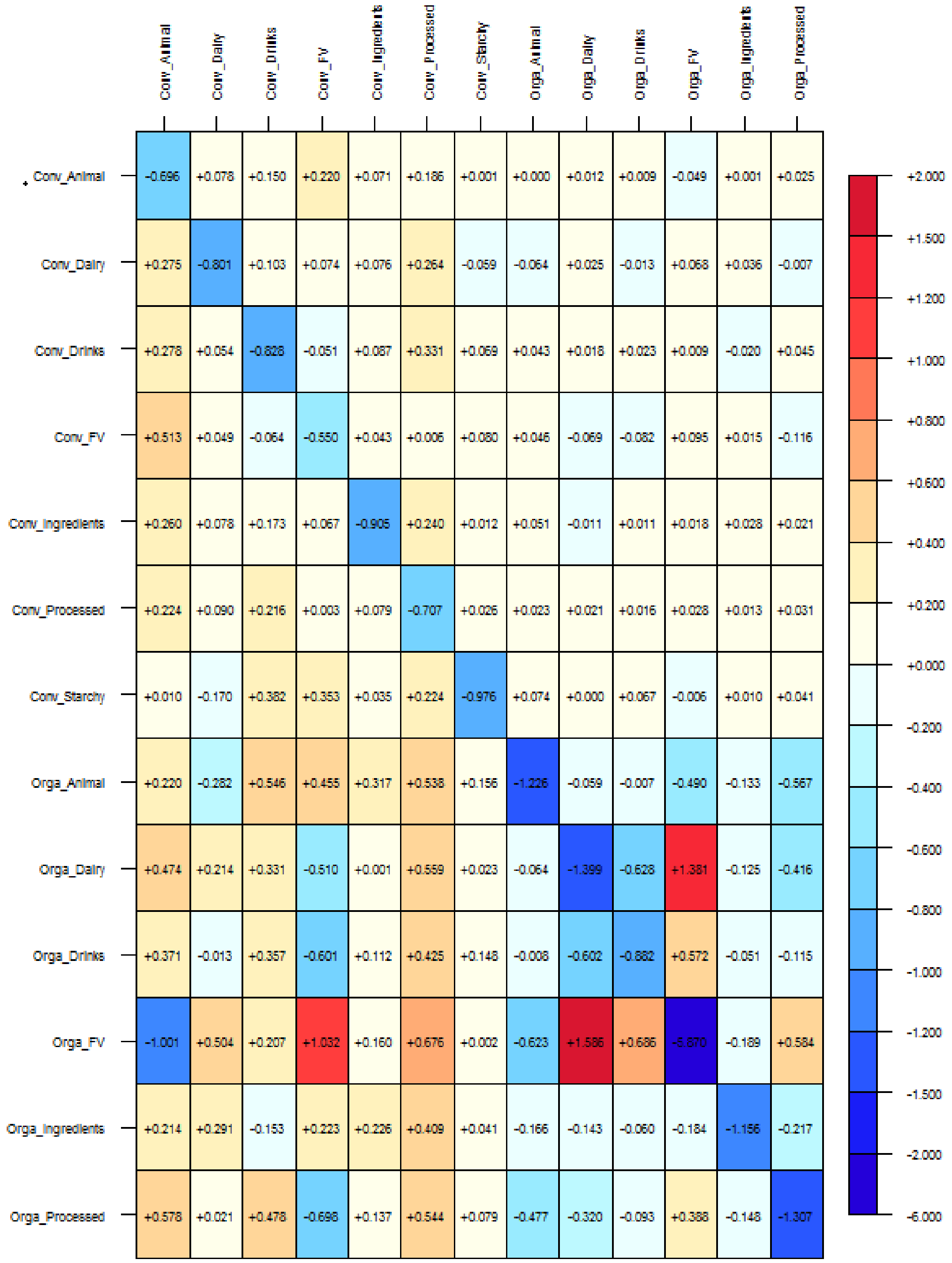
The Hicksian (compensated) elasticities are calculated as $e_{ij} = \frac{1}{\overline{w}_i}\widehat{\Phi}_i a_{ij} + \overline{w}_j - \Delta_{ij}$ where $\overline{w}_i$is the sample average observed budget share for i, $\widehat{\Phi}_i$ is the sample mean of the $\widehat{\Phi}_{hit}$ and Δ_{ij} is the Kronecker delta, with $\Delta_{ij} = 1\ if\ i = j$ (own-price elasticities) and $\Delta_{ij} = 0\ if\ i \neq j$ (cross-price elasticities) (Cardwell et al., 2015; Yen et al., 2002).

The expenditure elasticities are given by $\eta_i = \frac{\widehat{\Phi}_i(\sum_{r=1}^{L} rb_{ir} y_{ht}^{r-1}))}{\overline{w}_i} + 1$ where $\widehat{\Phi}_i(\sum_{r=1}^{L} rb_{ir} y_{ht}^{r-1})$ is the derivative of w_{hit} with respect to the real expenditures y_{ht} (Castellón et al., 2015; Yen et al., 2002).

The Marshallian (uncompensated) elasticities, accounting for income effects in addition to substitution effects, are obtained via the Slutsky equation: $e_{ij}^{*} = e_{ij} - \overline{w}_i\eta_i$.

4.4. Results and discussion

Figure 1. Hicksian price elasticities



4.4.1. Own-price elasticities

All the own-price elasticities (except the residual product family which is designed as inelastic) have the expected negative signs (Figure 1). The own-price elasticities for conventional products are moderate (-0.55 to -1), indicating that consumers are moderately responsive to price changes. The own-price elasticities are much larger for organic products (-1.2 to -5.9), with the exception of drinks (-0.9), showing that consumers purchasing organic products greatly adjust their purchases of organic products when prices evolve. The lower own-price elasticities of organic drinks may relate to strong habits and/or higher health or fair trade preoccupation: hot beverages (coffee, tea, infusions) indeed make up 40 % of the organic drinks category.

In a marketing study of price promotions in the USA, Bezawada and Pauwels (2013) also show that organic sales strongly increase when organic products' prices are lower and that the long term own-price elasticities of organic products are larger than conventional products' ones. Glaser et al. (1999) also find large own-price elasticities for several organic vegetables in the USA, ranging from -1.630 to -2.268, whereas the own-price elasticities for the same vegetables but in conventional quality only range from -0.102 to -1.043. Similarly, Lin et al. (2009) find own-price elasticities for organic fruits ranging from -1.06 to -3.54 while own-price elasticities for conventional fruits only range from -0.49 to -0.85.

4.4.2. Cross-price elasticities

83% of the cross-price elasticities of conventional products' families are positive (upper half of Figure 1), indicating that most conventional products are substitutes to both other conventional and organic products. These cross-price elasticities are mostly small however, attesting that price-driven substitutions are difficult between such large product families. These small elasticities also illustrate the selection process as a large share of the sample does not purchase the organic versions of products, the price of these organic products would have to greatly decrease to incite consumers who only purchase conventional products to start consuming organic products.

The case of the cross-elasticities between conventional fruits and vegetables and conventional animal products is worth highlighting as the value of this elasticity is larger, showing that F&V are substitutes to animal products.

For conventional products, H_1 is invalidated as conventional products are mostly substitutes among themselves, with small although positive cross price elasticities. However, H_2 is confirmed as the cross-price elasticities of conventional products with organics ones are close to zero.

The cross-price elasticities of organic products differ from those of conventional products. Indeed, most of these elasticities are of large absolute value and present a variety of signs. The cross-price elasticities of organic products with conventional products are mostly positive (83% of positive elasticities excluding the residual products' family), indicating that organic products are substitutes of conventional products.

The consumption of organic products is especially responsive to price changes of conventional F&V, animal and processed products, which validates H_3. Oppositely, the cross-price elasticities of organic products with other organic products are mostly negative (80% of negative elasticities) showing that organic products are complements among themselves and verifying H_1 for organic products.

This indicates that organic consumers seem to link their purchases from different families of products and that they would rather increase the quantity of organic food they consume proportionally in all products' families rather than on one specific family.

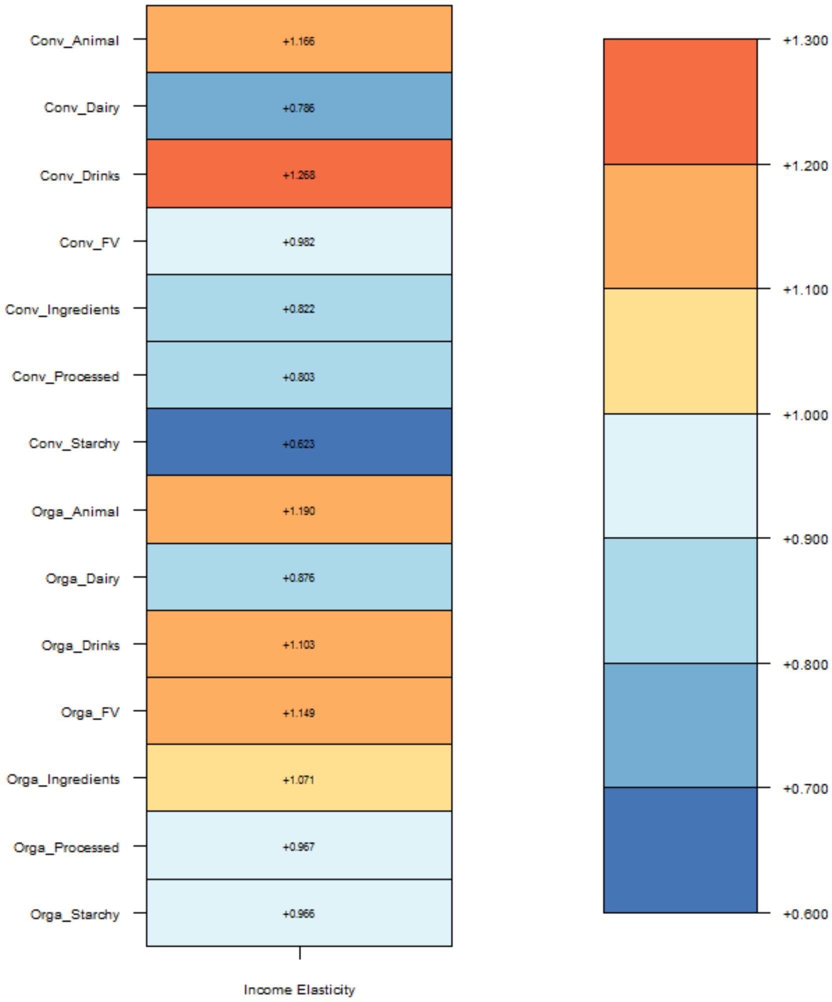
Organic F&V have especially large price-elasticities and also strongly influence the demand for other organic food (price elasticities of other organic foods with organic F&V are large). These large elasticities may be explained by the fact that organic F&V is the most purchased family of organic products: there are only 54% of zero purchases in our data vs. 73% on average for other organic product families. Thus, the demand for organic F&V is less censored and prices have more influence on their demand than the socio-demographics or the probits' distribution and density functions estimates from the first stage of the SY demand system.

This asymmetry between organic and conventional products' elasticities has also been observed by Glaser et al. (1999) for frozen vegetables in the USA. They find that elasticities of conventional products' demand in regards to organic products' prices are close to zero whereas the elasticities of organic products in regards to conventional prices are positive and ranging from 0.446 to 2.437. Glaser et al. (2000) and Alviola and Capps (2010) find similar results for organic and conventional milk consumption in the USA, organic milk is a strong substitute for conventional milk whereas conventional milk purchases are not influenced by organic milk prices. Zhang et al. (2011) demonstrate similar results for fresh organic and conventional vegetables in the USA.

The asymmetry of cross-price elasticities indicates that an increase of conventional products' prices (via a tax for example) would efficiently shift consumers' purchases from conventional to organic products whereas an increase of organic products' prices would not change consumers' behavior, i.e. would not strongly reduce organic food consumption. As observed by Lin et al. (2009) in the case of organic and conventional fruits in the USA, a change in the relative prices of organic and conventional products would strongly incite consumers to *cross-over* from conventional to organic products while it would less likely results in a *reverting* of organic purchases to conventional ones.

4.4.3. Expenditure elasticities

Figure 2. Expenditures elasticities



Conventional animal products and drinks appears– on average – as luxury goods, as the expenditures elasticities are slightly greater than unity (Figure 2). Thus, if an average consumer is able to spend more on food, he will relatively spend more of this additional expenditures on animal product and drinks (likely meat and alcohol). Most of the organic products are also luxury goods with the notable exception of dairy products which appears as normal goods. The other conventional and organic families of products have positive and lower than unity expenditures elasticities, ranging from 0.803 to 0.967, indicating that they are normal goods, i.e. if a household's food expenditures increase by 10%, he will increase its consumption of these normal goods, but by less than 10%.

Demonstrating that organic products' expenditures elasticities are close to unity reveals that income is not strongly limiting organic food consumption and that purchasing organic products is possible at any level of food expenditures, thus confirming the intuitions of Monier et al. (2009), Yiridoe et al. (2005) and Lambotte et al. (2020). Boizot-Szantai et al. (2017) have also shown that food expenditures are not strongly different (10% higher) between the highest and lowest quintile in term of organic consumption.

In addition, as food has an income elasticity close to 0 in respect to the whole households' expenditures (Benus et al., 1976), these results on expenditures elasticities can be extended to income elasticities.

4.4.4. Simulation of a price subvention for organic products

Using the Hicksian elasticities (e_{ij}) presented in Figure 1, we assess the impact of a subvention of organic food (i.e. a reduction of 20% of the price of organic products, assuming perfect transmission) on the budget shares of organic food. Our simulation is based on the budget shares of 2018 ($\overline{w}_i^{2018}$), and thus predict the budget shares after a subvention ($\overline{w}_i^{\emptyset SUBV}$) as $\overline{w}_i^{\emptyset SUBV} = \overline{w}_i^{2018}(1 + \sum_{j=1}^{J} e_{ij}\Delta p_j)$ where Δp_i is a vector of price changes, i.e. zero for conventional product and -20% for organic products. The 20% price decrease of organic products yields an increase in the demand of organic food of 40%. Nevertheless, the average budget share of organic food only reaches 5.9% after the subvention, which is far from the Green deal target (Table 2).

Table 2. Effects of a VAT exemption for organic products

Organic Product Family	Budget shares in 2018	Budget shares subvention	Variation (% increase)
Animal	0.6%	0.9%	50%
Dairy	0.3%	0.4%	25%
Drinks	0.6%	0.7%	22%
Fruits and Vegetables	0.7%	1.2%	77%
Cooking Ingredients	0.6%	0.9%	39%
Processed food	1.1%	1.5%	40%

The price subvention has a higher impact on organic product families which have relatively large own-price elasticities, i.e., animal products and F&V, which are thus more impacted by the subvention (+50% and +77% increase of their budget share after the VAT exemption compared to 2018 respectively). As the actual budget shares of organic products are really small compared to conventional products', the 20% price subvention has a weak absolute effect on organic food demand. A wider subsidization of organic food would be needed to reach the 25% target of the Green deal. However, organic product cannot be indefinitely subsidized due to government's tax burdens and because subsidizing organic products would only be efficient up to the point that organic food prices equal their conventional counterparts. Once such equilibrium is reached, the demand for organic products would not be related to prices anymore but rather to availability, consumption motives (health, environmental impacts, fair trade …) or purchasing and cooking habits. Our results tend to show that these factors could play a larger role than organic food prices in increasing organic food consumption to a substantial market share such as the 25% target of the Green deal.

4.4.5. Limits & future research

The main limit of these estimates is the absence of a stronger correction than the FI index for the quality bias in prices and for price endogeneity. Quality correction à la Cox and Wohlgenant (1986), regressing socio-demographics on the unit values and using the predicted unit values in the demand system, often produces unrealistic price estimates (negative prices) in our case, because for some organic products, we have few observations in a given time period. Products' availability has been used as an instrument for prices but our existing availability index may still too endogenous for this purpose (Allcott et al., 2019). This is nevertheless something that could be explored.

Another limit is the absence of a corrected computation of standard errors for the parameters of the two-step censored demand system. We intend to remedy to these issues in a future version of this paper, computing standard errors using a bootstrapping procedure (Castellón et al., 2015).

In the same direction, a verification of the different theoretical and computational assumptions related to demand system estimation in the SY two-step procedure would be useful for future research. An application and estimation of the censored model proposed by Zhen et al. (2014), would allow to verify our results and compare the estimated elasticities and standard errors between both models.

4.5. Conclusion

In an attempt to improve the understanding of organic consumers' behaviour, we estimate price and expenditures elasticities of organic and conventional food in France from 2011 to 2018 using Kantar® scanner data. We successfully develop a censored EASI demand system for 7 organic and conventional products' families.

We find that the own-price elasticities of organic products are considerably more than unity (in absolute values) and larger than conventional products' elasticities, indicating that consumers are willing to increase their consumption of organic products when organic prices decrease. We show that organic products are either luxury or normal goods, with expenditures elasticities close to unity in both cases. This indicates that expenditures, and more generally household's income, do not strongly affect organic food consumption.

Moreover, organic products are mostly complements among themselves as witnessed by the large share of negative cross-price elasticities between organic products' families. However, organic products appear as substitutes of conventional products, as shown by their positive cross-price elasticities.

Organic food demand is thus reactive to price changes of both organic and conventional products which indicates that a subvention of organic products or a tax of conventional products would increase consumption of organic food. We show that a price subvention of organic products, reducing organic prices by 20% (assuming a perfect transmission) would increase the market share of organic food by 40%, driven by animal products and F&V. Although this effect is large, it would only increase organic food market share from 4.3% in 2018 to 6% after the subvention, which is far from the Green deal target, i.e. a 25% market share for organic food.

Should such a pricing policy be enforced and which level of subvention and targets should be selected is still an open question, worth discussing in future research. Some areas worth questioning might include the advantages and disadvantages of taxing conventional products versus subsidizing organic products, in term of both farmers and consumers' welfares or estimating an optimal tax/subsidy level under nutritional, environmental and budget constraints.

4.6. Supplementary Materials.

SM 1. Descriptive information of the market of organic food from 2011 to 2018

Figure SM 1.a. Evolution of the market share of organic and conventional food from 2011 to 2018

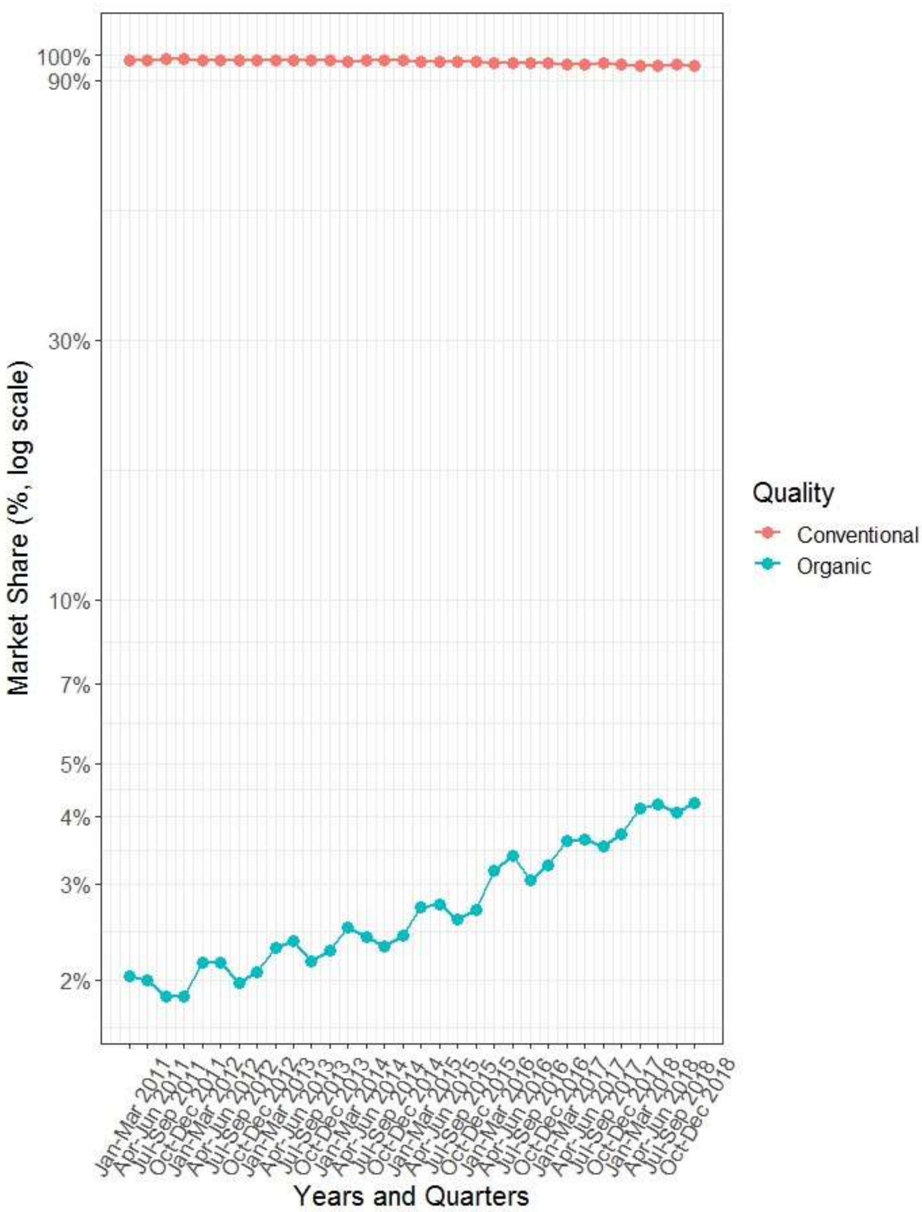


Figure SM 1.b. Evolution of the share of products' families in total organic expenditures

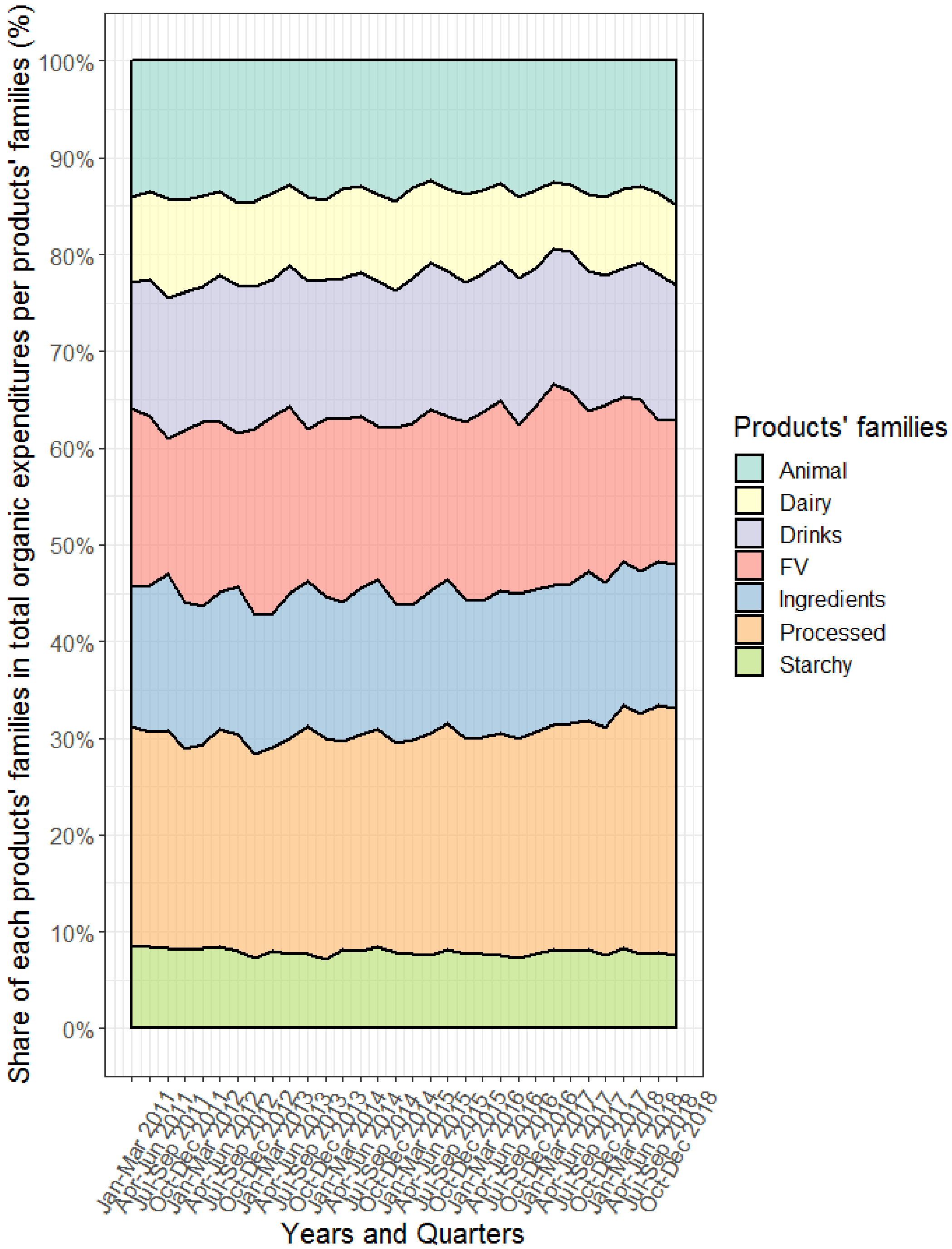
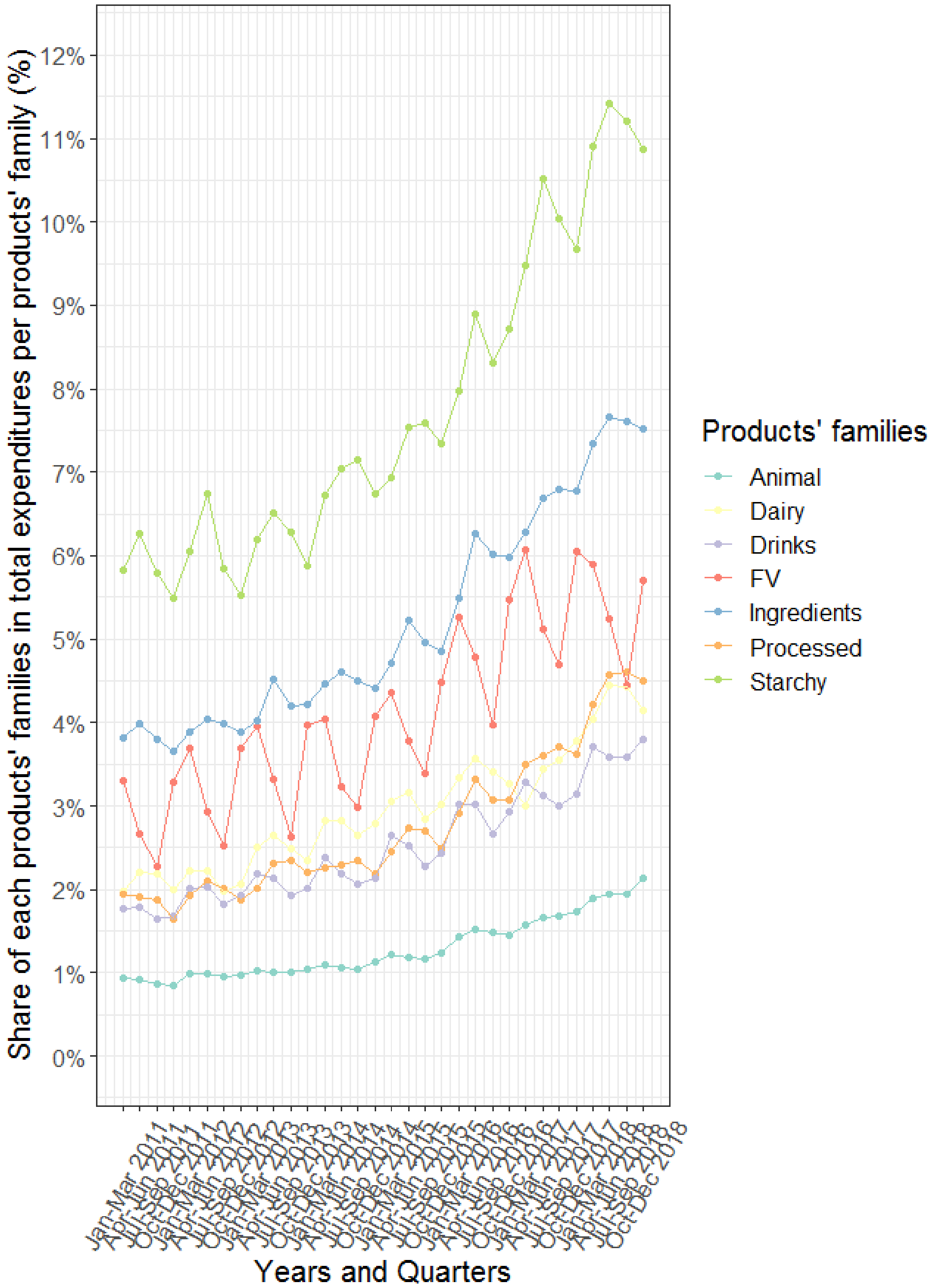


Figure SM 1.c. Evolution of the share of the organic version relatively to the conventional one for each products' families



SM 2. Products Aggregation into *families*

Family	Products	Conventional quality budget share in 2018	Organic Quality budget share in 2018
Animal	Meat, fish, eggs.	28.2%	0.6%
Dairy	Cheese, milk.	7.7%	0.3%
Drinks	Alcoholic drinks, coffee, tea, milk substitutes, water, juices, soda.	15.4%	0.6%
Fruits and Vegetables	Fresh, frozen and processed fruits and vegetables.	11.9%	0.7%
Cooking Ingredients	Fat, culinary ingredients, sweeteners, butter.	7.6%	0.6%
Processed food	Desserts, baby food, biscuits, pastries, prepared meals, confectionary, appetizers.	22.5%	1%
Starchy food	Bread, flour, cereals, pasta, pulses.	2.6%	0.3%

General Conclusion

Conclusion

This thesis has tried to deepen the current understanding of the consequences of a production and consumption shift toward quality food products. On one side, we have assessed the economic and environmental performances of quality-labelled farms compared to their conventional alternatives. On a second side, we have analyzed consumers' behavior toward quality food, with a focus on the regularity of organic consumption and organic price elasticities.

In the first chapter, we focus on PDO dairy farms and develop a model in order to include direct LUC in the estimation of farms' GHGE. Using a dataset of 95 LCA of dairy farms in *Savoy* and *Franche-Comté*, we reconstitute farms' cost, revenues and gross margin. We also simulate the direct land-use changes of these farms (soil carbon sequestration or emission) and the impact of several farming practices on carbon sequestration in order to estimate net GHGE. Although we could not find synergies between the economic (gross margin) and environmental (GHGE) performances of PDO dairy farms, we uncover several levers that improve one of the above-cited performance without compromising the other. Investing in equipment to more efficiently dry the hay or milk the cows, limit livestock density, or reduce fuel use increase the environmental performance by 5 to 13% without impairing gross margin. Increasing labor use or reducing the amount of protein in the diet enhance the economic performance by 7 to 21% without deteriorating the environmental performance. We show that integrating the effect of LUC and management practices in the assessment of farms' carbon footprint and proposing indicators of economic and environmental performances harmonized per liter of milk produced or per hectare of land used is key to robustly analyze the performances of dairy farms. Our results show that PDO farms, similarly to conventional farms, have antagonistic carbon footprint and economic margins, i.e. the farms with the lowest carbon footprint also have the lowest profitability. This indicates that encouraging certified dairy production may not create the win-win situation expected, especially because of the lower productivity of PDO farms and land-use changes, even if several levers could increase the performances of such farms.

In the second chapter, we continue our analysis of the economic and environmental performances of quality-labelled farming systems with a comparison of organic and conventional dairy farms in France. Using a similar dataset of the LCA of 3,191 dairy farms in France, we develop our model of theoretical land use change to integrate the estimation of indirect land use changes in addition to direct LUC and the impact of management practices on carbon sequestration. Moreover, using the extraordinary size of our dataset, we perform propensity score weighting to robustly control for the structural and pedo-climatic differences between organic and conventional farms. Doing so, we find that organic milk has a 8.6 – 29% lower carbon footprint than conventional milk, depending on whether indirect land use changes are accounted for. In addition, we could not find a significant difference between the gross margin of organic and conventional farms. We show that integrating a weighting or matching procedure in the comparison of the performances of different farming systems is crucial: for example, without weighting, the carbon footprint of organic milk is 39% lower instead of 29% and the conventional farms are significantly more profitable. We raise that integrating indirect LUC in LCA is complex and introduces uncertainty, which may explain why indirect LUC are sparsely included in the GHGE' estimates of food products. Finally, the results of this chapter on organic and conventional farms relativize our findings on PDO farms: all farming systems have an antagonism between their environmental and economics performances when LUC and carbon sequestration are accounting for. Thus, we cannot assert that either organic or PDO would be win-win dairy farming systems but we show that certified farms have lower carbon footprints that comparable conventional farms. This result alone justifies public policies attempting at developing certified agricultural systems to reduce territorial GHGE.

In the third chapter, we analyze purchase behavior of quality food consumers using several years of Kantar®'s scanner data (database of the purchases of 12,000 of households). We find that the consumption of geographical indications and label rouge food is always occasional while consumer attitude towards organic food is often *regular*: for a given product, consumers tend to either purchase it always organic or always conventional but not often a mix of both (*occasional*). More precisely, we uncover that 29% of the households are regular for at least one organic product although very few households are organic regulars for their entire basket. However, these regular organic consumers are key actors for marketing strategies or public policies as they are responsible for 28% of the purchases of the organic market and up to 50% for some fruits and vegetables, eggs or milk. Baby food, meal substitutes, desserts, bread and flour also show evidences of regular organic purchases behavior. Using a random utility modelling and a logit estimation, we show that regular organic consumers are in general more wealthy, urban, have a higher professional status, are more likely in couple and have relatively less children. Regular organic behavior is more prominent in products categories that are more widely available in all types of shops but does not seem influenced by the relative price of organic products compared to their conventional alternatives. The main motive behind this study of consumer behavior toward certified food through the prism of regularity was to analyze the duplication of regulars purchases among different products. Indeed, if regular purchases of a product are an entry point to wider transition to diets based on certified products, then public policies targeting the consumption of products for which regular purchases is common would be effective in increasing the consumption of certified food. However, our results indicate that regular purchases are not strongly duplicated. Nevertheless, increasing the availability of organic products in all the shopping sources and the information about the benefits of organic products on the health, environment or animal welfare seems to be effective public actions to increase regular behavior toward organic products and the overall consumption of organic food.

In the last chapter, we also use scanner data and apply a censored EASI demand system, in order to estimate price and expenditures elasticities of organic and conventional food in France from 2011 to 2018. We uncover that own-price elasticities of organic products are considerably larger than conventional products' elasticities, indicating that reducing the price of organic food would strongly increase its consumption. We also show that organic products can be mostly classified as luxury goods with expenditures elasticities slightly higher than unity, indicative of a rather small role of food expenditures and income in determining organic consumption. Moreover, organic products are complements among themselves (negative cross-price elasticities) but they are substitutes of conventional products (positive cross-price elasticities). Organic food demand is thus reactive to price changes and a price subvention of organic products would increase their market share by 40%. This final chapter presents complementary results to the third chapter in regards to the role of price in organic food consumption: whereas regular consumers' purchase decisions are not related to prices, occasional consumers are more reactive to price changes, especially for the conventional alternatives. The results of this chapter show that subventions of certified food, decreasing their relative price are effective public actions to increase the consumption of certified products and thus the transition to diets based on such quality products.

Limits and future research

This work however suffers some limits worth mentioning. First of all, the assessment of the economic and environmental performances of PDO and organic dairy farms is hindered by the omission of the farmers' knowledge and skills, which are not (and cannot be) observed in the LCA datasets we use. These omitting variables might create endogeneity in the regression models we applied and thus the causality of the relationships we identify must be carefully considered. Other methods, such as farm system modelling or Data Envelopment Analysis have been applied to similar context (Beukes et al., 2010; Doole, 2014; Iribarren et al., 2011) and could be used to increase the robustness of our results.

Secondly, the model we used to estimate GHGE from direct and indirect LUC is based on secondary data sources which comes with a high level of uncertainty at the farm level that we could not satisfactorily reduce. These usual values of dLUC/iLUC emission factors from the IPCC (2019) are based on national averages anc cannot account for the heterogeneity of farms. Using results such as ours in a bottom-up process to re-estimate such average values of dLUC and iLUC emission factors could improve the knowledge of farms' GHGE and help defining mitigation strategies.

Thirdly, gathering a panel database of farms' LCA instead of cross-sectional database could improve our estimation of the difference in economic and environmental performances between certified and conventional farms. Indeed, observing the same farms before and after their transitions from a conventional system to an organic one could yield precious information on the structural and performances' differences between both farming systems.

Lastly, our analysis of consumers' behavior toward quality food, and especially toward organic food did not identify transitions or shifts from a regular consumption of conventional products to a regular consumption of organic versions of these products. Defining a methodology to identify such transitions as well as the factors that hinder them would enlighten greatly the empirical understanding of consumers' preferences and purchasing behavior.

References

Abadie, A., Imbens, G., Kennedy, J.F., 2002. Simple and bias-corrected matching estimators for average treatment effect. NBER Technical Working Paper 0136789.

Agence Bio, 2019a. Les chiffres 2018 du secteur bio.

Agence Bio, 2019b. Baromètre 2018 de consommation et de perception des produits biologiques en France.

Agreste Bourgogne-France Comté, 2015. Les chiffres du lait 2015.

Allais, O., Bertail, P., Nichèle, V., 2010. The Effects of a Fat Tax on French Households' Purchases: A Nutritional Approach. American Journal of Agricultural Economics 92, 228–245. https://doi.org/10.1093/ajae/aap004

Allcott, H., Diamond, R., Dubé, J.-P., Handbury, J., Rahkovsky, I., Schnell, M., 2019. Food Deserts and the Causes of Nutritional Inequality*. The Quarterly Journal of Economics 134, 1793–1844. https://doi.org/10.1093/qje/qjz015

Alviola, P.A., Capps, O., 2010. Household demand analysis of organic and conventional fluid milk in the United States based on the 2004 Nielsen Homescan panel. Agribusiness n/a-n/a. https://doi.org/10.1002/agr.20227

Apostolidis, C., McLeay, F., 2016. Should we stop meating like this? Reducing meat consumption through substitution. Food Policy 65, 74–89. https://doi.org/10.1016/j.foodpol.2016.11.002

Augere-Granier, M., 2018. The EU dairy sector. Main features, challenges and prospects. Briefing of the European Parliament 12.

Baldini, C., Gardoni, D., Guarino, M., 2017. A critical review of the recent evolution of Life Cycle Assessment applied to milk production. Journal of Cleaner Production 140, 421–435. https://doi.org/10.1016/j.jclepro.2016.06.078

Banks, J., Blundell, R., Lewbel, A., 1997. Quadratic Engel Curves and Consumer Demand 85, 298–306.

Barrena, R., Sánchez, M., 2010. Frequency of consumption and changing determinants of purchase decision: from attributes to values in the organic food market. Spanish Journal of Agricultural Research 8, 251. https://doi.org/10.5424/sjar/2010082-1178

Baudry, J., Pointereau, P., Seconda, L., Vidal, R., Taupier-Letage, B., Langevin, B., Allès, B., Galan, P., Hercberg, S., Amiot, M.J., Boizot-Szantai, C., Hamza, O., Cravedi, J.P., Debrauwer, L., Soler, L.G., Lairon, D., Kesse-Guyot, E., 2019. Improvement of diet sustainability with increased level of organic food in the diet: Findings from the BioNutriNet cohort. American Journal of Clinical Nutrition 109, 1173–1188. https://doi.org/10.1093/ajcn/nqy361

Bellassen, V., Drut, M., Antonioli, F., Brečić, R., Diallo, A., Ferrer-lópez, H., Gauvrit, L., Hoang, V., Steinnes, K.K., Majewski, E., Malak-rawlikowska, A., Mattas, K., Nguyen, A., Papadopoulos, I., Peerlings, J., Ristic, B., Tomi, M., Corvinus, Á.T., 2021. The carbon and land footprint of certified food products. Journal of Agricultural and Food Industrial Organization.

Bellora, C., Bureau, J., 2016. How Green is Organic ? Indirect Environmental Effects of Making EU Agriculture Greener (Presented at the 19th Annual Conference on Global Economic Analysis, Washington DC, USA). Global Trade Analysis Project (GTAP), Department of Agricultural Economics, Purdue University, West Lafayette, IN.

Benus, J., Kmenta, J., Shapiro, H., 1976. The Dynamics of Household Budget Allocation to Food Expenditures. The Review of Economics and Statistics 58, 129. https://doi.org/10.2307/1924018

Bernard, J.C., Bernard, D.J., 2009. What Is It About Organic Milk? An Experimental Analysis. American Journal of Agricultural Economics 91, 826–836. https://doi.org/10.1111/j.1467-8276.2009.01258.x

Berry, B.Y.S., Levinsohn, J., Pakes, A., 1995. Automobile Prices in Market Equilibrium. Econometrica 63, 841–890.

Beukes, P.C., Gregorini, P., Romera, A.J., Levy, G., Waghorn, G.C., 2010. Improving production efficiency as a strategy to mitigate greenhouse gas emissions on pastoral dairy farms in New Zealand. Agriculture, Ecosystems and Environment 136, 358–365. https://doi.org/10.1016/j.agee.2009.08.008

Bezawada, R., Pauwels, K., 2013. What is Special about Marketing Organic Products? How Organic Assortment, Price, and Promotions Drive Retailer Performance. Journal of Marketing 77, 31–51. https://doi.org/10.1509/jm.10.0229

Boizot-Szantai, C., Hamza, O., Soler, L.G., 2017. Organic consumption and diet choice: An analysis based on food purchase data in France. Appetite 117, 17–28. https://doi.org/10.1016/j.appet.2017.06.003

Bonesmo, H., Beauchemin, K.A., Harstad, O.M., Skjelvåg, A.O., 2013. Greenhouse gas emission intensities of grass silage based dairy and beef production: A systems analysis of Norwegian farms. Livestock Science 152, 239–252. https://doi.org/10.1016/j.livsci.2012.12.016

Boonsaeng, T., Carpio, C.E., Boonsaeng, T., Carpio, C.E., 2019. A Comparison of Food Demand Estimation from Homescan and Consumer Expenditure Survey Data. https://doi.org/10.22004/AG.ECON.281316

Bouamra-Mechemache, Z., Chaaban, J., 2010. Determinants of adoption of protected designation of origin label: Evidence from the french brie cheese industry. Journal of Agricultural Economics 61, 225–239. https://doi.org/10.1111/j.1477-9552.2009.00234.x

Buder, F., Feldmann, C., Hamm, U., 2014. Why regular buyers of organic food still buy many conventional products: Product-specific purchase barriers for organic food consumers. British Food Journal 116, 390–404. https://doi.org/10.1108/BFJ-04-2012-0087

Bunte, F., Van Galen, M., Kuiper, E., Bakker, J., 2007. Limits to growth in organic sales Price elasticity of consumer demand for organic food in Dutch supermarkets.

Caillavet, F., Fadhuile, A., Nichèle, V., 2016. Taxing animal-based foods for sustainability: Environmental, nutritional and social perspectives in France. European Review of Agricultural Economics 43, 557–560. https://doi.org/10.1093/erae/jbv041

Cardwell, R., Lawley, C., Xiang, D., 2015. Milked and Feathered: The Regressive Welfare Effects of Canada’s Supply Management Regime. Canadian Public Policy 41, 1–14. https://doi.org/10.3138/cpp.2013-062

Castellón, C.E., Boonsaeng, T., Carpio, C.E., 2015. Demand system estimation in the absence of price data: an application of Stone-Lewbel price indices. Applied Economics 47, 553–568. https://doi.org/10.1080/00036846.2014.975332

Cederberg, C., Flysjo, A., 2004. Life cycle inventory of 23 dairy farms in South-Western Sweden, SIK Rapport.

Cederberg, C., Mattsson, B., 2000. Life cycle assessment of milk production - a comparison of conventional and organic farming. Journal of Cleaner Production 8, 49–60. https://doi.org/10.1016/S0959-6526(99)00311-X

Cederberg, C., Mattsson, B., 1999. Life Cycle assessment of Swedish milk production - a comparison of conventional farming. Journal of Cleaner Production 8, 49–60.

Chekima, B., Oswald, A.I., Wafa, S.A.W.S.K., Chekima, K., 2017. Narrowing the gap: Factors driving organic food consumption. Journal of Cleaner Production 166, 1438–1447. https://doi.org/10.1016/j.jclepro.2017.08.086

Chever, T., Renault, C., Renault, S., Romieu, V., 2012. Value of production of agricultural products and foodstuffs, wines, aromatised wines and spirits protected by a geographical indication (GI). Final report to the European Commission, TENDER N° AGRI–2011–EVAL–04 85.

Clark, M., Tilman, D., 2017. Comparative analysis of environmental impacts of agricultural production systems, agricultural input efficiency, and food choice. Environ. Res. Lett. 12, 064016. https://doi.org/10.1088/1748-9326/aa6cd5

Cotation des gros bovins entrée abattoir (1993 - 2017), 2017. , Service régional de l'information statistique et économique. DRAAF Bourgogne France-Comté.

Cox, T.L., Wohlgenant, M.K., 1986. Prices and Quality Effects in Cross-Sectional Demand Analysis. American Journal of Agricultural Economics 68, 908–919. https://doi.org/10.2307/1242137

Crowder, D.W., Reganold, J.P., 2015. Financial competitiveness of organic agriculture on a global scale. Proceedings of the National Academy of Sciences of the United States of America 112, 7611–7616. https://doi.org/10.1073/pnas.1423674112

Deaton, A., 1988. Quality, Quantity, and Spatial Variation of Price. American Economic Review 78, 418–430. https://doi.org/10.2307/1809142

Dessart, F.J., Barreiro-Hurlé, J., van Bavel, R., 2019. Behavioural factors affecting the adoption of sustainable farming practices: a policy-oriented review. European Review of Agricultural Economics 46, 417–471. https://doi.org/10.1093/erae/jbz019

Diewert, W.E., 1998. Index Number Issues in the Consumer Price Index. Journal of Economic Perspectives 12, 47–58. https://doi.org/10.1257/jep.12.1.47

Dillon, P., Crosse, S., O'Brien, B., Mayes, R.W., 2002. The effect of forage type and level of concentrate supplementation on the performance of spring-calving dairy cows in early lactation. Grass and Forage Science 57, 212–223. https://doi.org/10.1046/j.1365-2494.2002.00319.x

Dimitri, C., Dettmann, R.L., 2012. Organic food consumers: What do we really know about them? British Food Journal 114, 1157–1183. https://doi.org/10.1108/00070701211252101

Dollé, J.-B., Moreau, S., Foray, S., 2013. Combiner production et environnement, un défi pour la filière laitière Les enjeux environnementaux majeurs Les enjeux relatifs au changement 1–16.

Doole, G.J., 2014. Least-cost greenhouse gas mitigation on New Zealand dairy farms. Nutrient Cycling in Agroecosystems 98, 235–251. https://doi.org/10.1007/s10705-014-9608-y

Drichoutis, A.C., Klonaris, S., Lazaridis, P., Nayga, R.M., 2008. Household food consumption in Turkey: a comment. European Review of Agricultural Economics 35, 93–98. https://doi.org/10.1093/erae/jbn010

Edjabou, L.D., Smed, S., 2013. The effect of using consumption taxes on foods to promote climate friendly diets - The case of Denmark. Food Policy 39, 84–96. https://doi.org/10.1016/j.foodpol.2012.12.004

EFESE, 2019. La séquestration de carbon par les écosystèmes en France.

European Commission, 2020. A Farm to Fork Strategy for a fair, healthy and environmentally-friendly food system.

European Commission, 2013. Organic versus conventional farming, which performs better financially ? Farm Economic Brief 1–10.

European Commission, 2008. COMMISSION REGULATION (EC) No 889/2008 of 5 September 2008 laying down detailed rules for the implementation of Council Regulation (EC) No 834/2007 on organic production and labelling oforganic products with regard to organic production, labelling and con. Official Journal of the European Union.

European Environment Agency, 2018. European waters Assessment of status and pressures 2018, Technical Report. https://doi.org/10.4324/9780203938607

Eurostat, 2018. Selling prices of agricultural products (absolute prices).

Eze, S., Palmer, S.M., Chapman, P.J., 2018. Soil organic carbon stock in grasslands: Effects of inorganic fertilizers, liming and grazing in different climate settings. Journal of Environmental Management 223, 74–84. https://doi.org/10.1016/j.jenvman.2018.06.013

Ferrier, P.M., Zhen, C., Ferrier, P.M., Zhen, C., 2017. The Role of Income in Explaining the Shift from Preserved to Fresh Vegetable Purchases. https://doi.org/10.22004/AG.ECON.264065

Fiore, M., Spada, A., Contò, F., Pellegrini, G., 2018. GHG and cattle farming: CO-assessing the emissions and economic performances in Italy. Journal of Cleaner Production 172, 3704–3712. https://doi.org/10.1016/j.jclepro.2017.07.167

Flysjö, A., Cederberg, C., Henriksson, M., Ledgard, S., 2012. The interaction between milk and beef production and emissions from land use change - Critical considerations in life cycle assessment and carbon footprint studies of milk. Journal of Cleaner Production 28, 134–142. https://doi.org/10.1016/j.jclepro.2011.11.046

Fornara, D.A., Tilman, D., Houlton, B.Z., 2012. Soil carbon sequestration in prairie grasslands increased by chronic nitrogen addition. Ecology 93, 2030–2036. https://doi.org/10.1890/12-0292.1

Fourmouzi, V., Genius, M., Midmore, P., 2012. The Demand for Organic and Conventional Produce in London, UK: A System Approach. Journal of Agricultural Economics 63, 677–693. https://doi.org/10.1111/j.1477-9552.2012.00353.x

Froehlich, A.G., Melo, A.S.S.A., Sampaio, B., 2018. Comparing the Profitability of Organic and Conventional Production in Family Farming: Empirical Evidence From Brazil. Ecological Economics 150, 307–314. https://doi.org/10.1016/j.ecolecon.2018.04.022

Gac, A., Agabriel, J., Dollé, J.-B., Faverdin, P., Van Der Werf, H., 2014. Le potentiel d'atténuation des gaz à effet de serre en productions bovines. Innovations Agronomiques 37, 67–81.

Gerber, P.J., Steinfeld, H., Henderson, B., Mottet, A., Opio, C., Dijkman, J., Falcucci, A., Tempio, G., 2013. Tackling climate change through livestock – A global assessment of emissions and mitigation opportunities, FAO. https://doi.org/10.1016/j.anifeedsci.2011.04.074

Glaser, L.K., Thompson, G.D., Glaser, L.K., Thompson, G.D., 2000. Demand for organic and conventional beverage milk Western Agricultural Economics Association Annual Meetings,. https://doi.org/10.22004/AG.ECON.36346

Glaser, L.K., Thompson, G.D., Glaser, L.K., Thompson, G.D., 1999. Demand for organic and conventional frozen vegetables. https://doi.org/10.22004/AG.ECON.21583

Gracia, A., de Magistris, T., 2008. The demand for organic foods in the South of Italy: A discrete choice model. Food Policy 33, 386–396. https://doi.org/10.1016/j.foodpol.2007.12.002

Guerci, M., Bava, L., Zucali, M., Tamburini, A., Sandrucci, A., 2014. Effect of summer grazing on carbon footprint of milk in Italian Alps: A sensitivity approach. Journal of Cleaner Production 73, 236–244. https://doi.org/10.1016/j.jclepro.2013.11.021

Guerci, M., Knudsen, M.T., Bava, L., Zucali, M., Schönbach, P., Kristensen, T., 2013. Parameters affecting the environmental impact of a range of dairy farming systems in Denmark, Germany and Italy. Journal of Cleaner Production 54, 133–141. https://doi.org/10.1016/j.jclepro.2013.04.035

Haas, G., Wetterich, F., Köpke, U., 2001. Comparing intensive, extensified and organic grassland farming in southern Germany by process life cycle assessment. Agriculture, Ecosystems and Environment 83, 43–53. https://doi.org/10.1016/S0167-8809(00)00160-2

Hao, X., Chang, C., Larney, F.J., 2004. Carbon, Nitrogen Balances and Greenhouse Gas Emission during Cattle Feedlot Manure Composting. Journal of Environemntal Quality 37–44.

Heien, D., Wessells, C.R., 1990. Demand systems estimation with microdata: A censored regression approach. Journal of Business and Economic Statistics 8, 365–371. https://doi.org/10.1080/07350015.1990.10509807

Herrero, M., Havlik, P., Valin, H., Notenbaert, A., Rufino, M.C., Thornton, P.K., Blummel, M., Weiss, F., Grace, D., Obersteiner, M., 2013. Biomass use, production, feed efficiencies, and greenhouse gas emissions from global livestock systems. Proceedings of the National Academy of Sciences 110, 20888–20893. https://doi.org/10.1073/pnas.1308149110

Herrero, Mario, Havlík, P., Valin, H., Notenbaert, A., Rufino, M.C., Thornton, P.K., Blümmel, M., Weiss, F., Grace, D., Obersteiner, M., 2013. Biomass use, production, feed efficiencies, and greenhouse gas emissions from global livestock systems. Proceedings of the National Academy of Sciences of the United States of America 110, 20888–20893. https://doi.org/10.1073/pnas.1308149110

Hiederer, R., Ramos, F., Capitani, C., Koeble, R., Blujdea, V., Gomez, O., Mulligan, D., Marelli, L., 2010. Biofuels: A New Methodology to Estimate GHG Emissions from Indirect Land Use Change. JRC Scientific and Policy Reports.

Hill, H., Lynchehaun, F., 2002. Organic milk: Attitudes and consumption patterns. British Food Journal 104, 526–542. https://doi.org/10.1108/00070700210434570

Hocquette, J.F., Gigli, S., 2005. Indicators of Milk and Beef Quality. https://doi.org/10.3920/978-90-8686-537-6

Hörtenhuber, S., Lindenthal, T., Amon, B., Markut, T., Kirner, L., Zollitsch, W., 2010. Greenhouse gas emissions from selected Austrian dairy production systems - Model calculations considering the effects of land use change. Renewable Agriculture and Food Systems 25, 316–329. https://doi.org/10.1017/S1742170510000025

Hughner, R.S., McDonagh, P., Prothero, A., Shultz II, C.J., Stanton, J., 2007. Who are organic food consumers? A compilation and review of why people purchase organic food. Journal of Consumer Behaviour.

INAO, 2019. Les produits sous signe d’identification de la qualité et de l’origine. Chiffres-Clés 2018.

Institut de L’Elevage, 2013. GUIDE MÉTHOLOGIQUE CAP’2ER ® : Calcul Automatisé des Performances Environnementales en Elevage de Ruminants 1–12.

IPCC, 2019. 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Chapter 4: Agriculture, Forestry and Other Land Uses (AFOLU). IGES, Hayama, Japan.

Iribarren, D., Hospido, A., Moreira, M.T., Feijoo, G., 2011. Benchmarking environmental and operational parameters through eco-efficiency criteria for dairy farms. Science of the Total Environment 409, 1786–1798. https://doi.org/10.1016/j.scitotenv.2011.02.013

Jonas, A., Roosen, J., 2008. Demand for milk labels in Germany: organic milk, conventional brands, and retail labels. Agribusiness 24, 192–206. https://doi.org/10.1002/agr.20155

Kasteridis, P., Yen, S.T., 2012. U.S. demand for organic and conventional vegetables: A Bayesian censored system approach. Australian Journal of Agricultural and Resource Economics 56, 405–425. https://doi.org/10.1111/j.1467-8489.2012.00589.x

Kesse-Guyot, E., Péneau, S., Méjean, C., Szabo de Edelenyi, F., Galan, P., Hercberg, S., Lairon, D., 2013. Profiles of Organic Food Consumers in a Large Sample of French Adults: Results from the Nutrinet-Santé Cohort Study. PLoS ONE 8. https://doi.org/10.1371/journal.pone.0076998

Kiefer, L., Menzel, F., Bahrs, E., 2014. The effect of feed demand on greenhouse gas emissions and farm profitability for organic and conventional dairy farms. Journal of Dairy Science 97, 7564–7574. https://doi.org/10.3168/jds.2014-8284

Kop, P. Van De, Sautier, D., Eds, A.G., 2006. Origin-based Products: Lessons for pro-poor market development. Royal Tropical Institute - CIRAD 53–63.

Kristensen, T., Mogensen, L., Knudsen, M.T., Hermansen, J.E., 2011. Effect of production system and farming strategy on greenhouse gas emissions from commercial dairy farms in a life cycle approach. Livestock Science 140, 136–148. https://doi.org/10.1016/j.livsci.2011.03.002

Lacour, C., Seconda, L., Allès, B., Hercberg, S., Langevin, B., Pointereau, P., Lairon, D., Baudry, J., Kesse-Guyot, E., 2018a. Environmental Impacts of Plant-Based Diets: How Does Organic Food Consumption Contribute to Environmental Sustainability? Frontiers in Nutrition 5, 1–13. https://doi.org/10.3389/fnut.2018.00008

Lacour, C., Seconda, L., Allès, B., Hercberg, S., Langevin, B., Pointereau, P., Lairon, D., Baudry, J., Kesse-Guyot, E., 2018b. Environmental Impacts of Plant-Based Diets: How Does Organic Food Consumption Contribute to Environmental Sustainability? Frontiers in Nutrition 5, 1–13. https://doi.org/10.3389/fnut.2018.00008

LaFrance, J.T., 1990. Incomplete Demand Systems and Semilogarithmic Demand Models. Australian Journal of Agricultural Economics 34, 118–131. https://doi.org/10.1111/j.1467-8489.1990.tb00697.x

Lambotte, M., De Cara, S., Bellassen, V., 2020. Once a quality food consumer, always a quality food consumer ? Consumption patterns of organic, label rouge and geographical indications in French scanner data. Review of Agricultural, Food and Environmental Studies. https://doi.org/Review of Agricultural, Food and Environmental Studies https://doi.org/10.1007/s41130-020-00121-z

Lambotte, M., De Cara, S., Brocas, C., Bellassen, V., 2021. Carbon footprint and economic performance of dairy farms: The case of protected designation of origin farms in France. Agricultural Systems 186, 102979. https://doi.org/10.1016/j.agsy.2020.102979

Lancaster, K.J., 1966. A new approach to consumer theory. Journal of political economy 74, 132–157.

Lansink, A.O., 2002. Effciency and productivity of conventional and organic farms in Finland 1994-1997. European Review of Agriculture Economics 29, 51–65. https://doi.org/10.1093/erae/29.1.51

Latruffe, L., Nauges, C., 2014. Technical efficiency and conversion to organic farming: the case of France. European Review of Agricultural Economics 41, 227–253. https://doi.org/10.1093/erae/jbt024

Lechenet, M., Makowski, D., Py, G., Munier-Jolain, N., 2016. Profiling farming management strategies with contrasting pesticide use in France. Agricultural Systems 149, 40–53. https://doi.org/10.1016/j.agsy.2016.08.005

Ledgard, S.F., Falconer, S.J., Abercrombie, R., Philip, G., Hill, J.P., 2020. Temporal, spatial, and management variability in the carbon footprint of New Zealand milk. Journal of Dairy Science 103, 1031–1046. https://doi.org/10.3168/jds.2019-17182

Les fromages de Savoie, 2017. Prix du Lait 2017.

Lewbel, A., Pendakur, K., 2009. Tricks with hicks: The EASI demand system. American Economic Review 99, 827–863. https://doi.org/10.1257/aer.99.3.827

Liang, D., Cabrera, V.E., 2015. Optimizing productivity, herd structure, environmental performance, and profitability of dairy cattle herds. Journal of Dairy Science 98, 2812–2823. https://doi.org/10.3168/jds.2014-8856

Lin, B.H., Yen, S.T., Huang, C.L., Smith, T.A., 2009. U.S. demand for organic and conventional fresh fruits: The roles of income and price. Sustainability 1, 464–478. https://doi.org/10.3390/su1030464

Lopez, E., Lopez, R.A., 2009. Demand for differentiated milk products: implications for price competition. Agribusiness 25, 453–465. https://doi.org/10.1002/agr.20219

Lovett, D.K., Shalloo, L., Dillon, P., O'Mara, F.P., 2008. Greenhouse gas emissions from pastoral based dairying systems: The effect of uncertainty and management change under two contrasting production systems. Livestock Science 116, 260–274. https://doi.org/10.1016/j.livsci.2007.10.016

Lovett, D.K., Shalloo, L., Dillon, P., O'Mara, F.P., 2006. A systems approach to quantify greenhouse gas fluxes from pastoral dairy production as affected by management regime. Agricultural Systems 88, 156–179. https://doi.org/10.1016/j.agsy.2005.03.006

Mäder, P., Fliebbach, A., Dubois, D., Gunst, L., Fried, P., Niggli, U., 2002. Soil Fertility and Biodiversity in Organic Farming. Science 296, 1694–1698.

Marian, L., Chrysochou, P., Krystallis, A., Thøgersen, J., 2014. The role of price as a product attribute in the organic food context: An exploration based on actual purchase data. Food Quality and Preference 37, 52–60. https://doi.org/10.1016/j.foodqual.2014.05.001

Massey, M., O'Cass, A., Otahal, P., 2018. A meta-analytic study of the factors driving the purchase of organic food. Appetite 125, 418–427. https://doi.org/10.1016/j.appet.2018.02.029

Masson-Delmotte, V., Pörtner, H.-O., Skea, J., Zhai, P., Roberts, D., Shukla, P.R., Pirani, A., Pidcock, R., Chen, Y., Lonnoy, E., Moufouma-Okia, W., Péan, C., Connors, S., Matthews, J.B.R., Zhou, X., Gomis, M.I., Maycock, T., Tignor, M., Waterfield, T., 2018. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty.

Maxwell, S.L., Fuller, R.A., Brooks, T.M., Watson, J.E.M., 2016. Biodiversity: The ravages of guns, nets and bulldozers. Nature 536, 143–145. https://doi.org/10.1038/536143a

McCaffrey, D.F., Ridgeway, G., Morral, A.R., 2004. Propensity score estimation with boosted regression for evaluating causal effects in observational studies. Psychological Methods 9, 403–425. https://doi.org/10.1037/1082-989X.9.4.403

McFadden, D., 2001. Economic Choices. American Economic Review 91, 351–378.

Meier, M.S., Stoessel, F., Jungbluth, N., Juraske, R., Schader, C., Stolze, M., 2015. Environmental impacts of organic and conventional agricultural products - Are the differences captured by life cycle assessment? Journal of Environmental Management 149, 193–208. https://doi.org/10.1016/j.jenvman.2014.10.006

Michaud, Q., 2016. Mise en place d'une démarche d'évaluation et d'amélioration du bilan carbone des exploitations agricoles.

Midler, E., Depeyrot, J.-N., Detang-Dessendre, C., 2019. Performance environnementale des exploitations agricoles et emploi 35.

Ministère de la Transition Ecologique et Solidaire, 2018. National Low Carbon Strategy Project: The ecological and inclusive transition towards carbon neutrality 144.

Ministère de l'Agriculture et de l'Alimentation, 2017. Les matières premières dans les aliments composés pour animaux de ferme en 2015. (No. 345), Agreste Primeur.

Mondelaers, K., Aertsens, J., Van Huylenbroeck, G., 2009. A meta-analysis of the differences in environmental impacts between organic and conventional farming. British Food Journal 111, 1098–1119. https://doi.org/10.1108/00070700910992925

Monier, S., Hassan, D., Nichle, V., Simioni, M., 2009. Organic food consumption patterns. Journal of Agricultural and Food Industrial Organization 7. https://doi.org/10.2202/1542-0485.1269

Monier-Dilhan, S., Poméon, T., Böhm, M., Brečić, R., Csillag, P., Donati, M., Ferrer-Pérez, H., Gauvrit, L., Gil, J.M., Hoàng, V., Lilavanichakul, A., Majewski, E., Malak-Rawlikowska, A., Mattas, K., Napasintuwong, O., Nguyễn, A.Q., Nikolaou, K., Papadopoulos, I., Pascucci, S., Peerlings, J., Ristic, B., Steinnes, K., Stojanovic, Z., Tomić Maksan, M., Török, Á., Veneziani, M., Vittersø, G., Bellassen, V., 2020. Do Food Quality Schemes and Net Price Premiums Go Together? Journal of Agricultural & Food Industrial Organization 0, 20190044. https://doi.org/10.1515/jafio-2019-0044

Muellbauer, J., 1974. Household composition, Engel curves and welfare comparisons between households. A duality approach. European Economic Review 5, 103–122. https://doi.org/10.1016/0014-2921(74)90018-X

Muller, A., Schader, C., El-Hage Scialabba, N., Brüggemann, J., Isensee, A., Erb, K.H., Smith, P., Klocke, P., Leiber, F., Stolze, M., Niggli, U., 2017. Strategies for feeding the world more sustainably with organic agriculture. Nature Communications 8, 1–13. https://doi.org/10.1038/s41467-017-01410-w

Muth, M.K., Okrent, A.M., Zhen, C., Karns, S.A., 2020. Estimating food demand systems using scanner data, Using Scanner Data for Food Policy Research. https://doi.org/10.1016/b978-0-12-814507-4.00006-7

Ngobo, P.V., 2011. What Drives Household Choice of Organic Products in Grocery Stores? Journal of Retailing 87, 90–100. https://doi.org/10.1016/j.jretai.2010.08.001

Oates, L., Cohen, M., Braun, L., 2012. Characteristics and consumption patterns of Australian organic consumers. Journal of the Science of Food and Agriculture 92, 2782–2787. https://doi.org/10.1002/jsfa.5664

O'Brien, D., Capper, J.L., Garnsworthy, P.C., Grainger, C., Shalloo, L., 2014. A case study of the carbon footprint of milk from high-performing confinement and grass-based dairy farms. Journal of Dairy Science 97, 1835–1851. https://doi.org/10.3168/jds.2013-7174

O'Brien, D., Hennessy, T., Moran, B., Shalloo, L., 2015. Relating the carbon footprint of milk from Irish dairy farms to economic performance. Journal of Dairy Science 98, 7394–7407. https://doi.org/10.3168/jds.2014-9222

Olesen, J.E., Schelde, K., Weiske, A., Weisbjerg, M.R., Asman, W.A.H., Djurhuus, J., 2006. Modelling greenhouse gas emissions from European conventional and organic dairy farms. Agriculture, Ecosystems and Environment 112, 207–220. https://doi.org/10.1016/j.agee.2005.08.022

Olivia, S., Gibson, J., 2003. Unit value biases in meat demand in Indonesia. Australian Agricultural and Resource Economics Society 2003 Annual Conference (47th).

Onyango, B.M., Hallman, W.K., Bellows, A.C., 2007. Purchasing organic food in US food systems: A study of attitudes and practice. British Food Journal 109, 399–411. https://doi.org/10.1108/00070700710746803

Overmars, K., Edwards, R., Padella, M., Prins, A.G., Marelli, L., 2015. Estimates of indirect land use change from biofuels based on historical data, JRC Scientific and Policy Reports. https://doi.org/10.2790/3647

Padel, S., Foster, C., 2005. Exploring the gap between attitudes and behaviour: Understanding why consumers buy or do not buy organic food. British Food Journal 107, 606–625. https://doi.org/10.1108/00070700510611002

Padilla Bravo, C., Cordts, A., Schulze, B., Spiller, A., 2013. Assessing determinants of organic food consumption using data from the German National Nutrition Survey II. Food Quality and Preference 28, 60–70. https://doi.org/10.1016/j.foodqual.2012.08.010

Pearson, D., Henryks, J., Sultan, P., Anisimova, T., 2013. Organic food : Exploring purchase frequency to explain consumer behaviour. Journal of Organic Systems 8, 50–63.

Pellerin, S., Bamière, L., Angers, D., Béline, F., Benoît, M., Butault, J.P., Chenu, C., Colnenne-David, C., De Cara, S., Delame, N., Doreau, M., Dupraz, P., Faverdin, P., Garcia-Launay, F., Hassouna, H., Hénault, C., Jeuffroy, M.H., Klumpp, K., Metay, A., Moran, D., Recous, S, Pardon, L., 2013. Quelle Contribution De L'Agriculture Française À La Réduction Des Émissions De Gaz À Effet De Serre ?

Pellerin, S., Bamière, L., Launay, C., 2019. Stocker du carbone dans les sols français, Quel potentiel au regard de l'objectif 4 pour 1000 et à quel coût? Synthèse du rapport d'étude, INRA (France) 114.

Pendakur, K., 2009. EASI made easier, Contributions to Economic Analysis. Elsevier. https://doi.org/10.1108/S0573-8555(2009)0000288010

Perrard, V., 2016. Mise en place d'une démarche d'évaluation et d'amélioration du bilan carbone des exploitations agricoles.

Plevin, R.J., O'Hare, M., Jones, A.D., Torn, M.S., Gibbs, H.K., 2010. Greenhouse gas emissions from biofuels' indirect land use change are uncertain but may be much greater than previously estimated. Environmental Science and Technology 44, 8015–8021. https://doi.org/10.1021/es101946t

Poeplau, C., Don, A., 2013. Sensitivity of soil organic carbon stocks and fractions to different land-use changes across Europe. Geoderma 192, 189–201. https://doi.org/10.1016/j.geoderma.2012.08.003

Pollak, R.A., Wales, T.J., 1981. Demographic Variables in Demand Analysis. Econometrica 49, 1533–1551.

R Core Team, 2020. R: A Language and Environment for Statistical Computing.

Rana, J., Paul, J., 2017. Consumer behavior and purchase intention for organic food: A review and research agenda. Journal of Retailing and Consumer Services 38, 157–165. https://doi.org/10.1016/j.jretconser.2017.06.004

Reganold, J.P., Wachter, J.M., 2016. Organic agriculture in the twenty-first century. Nature Publishing Group 2, 1–8. https://doi.org/10.1038/nplants.2015.221

Ridgeway, G., 2020. Generalized Boosted Models: A guide to the gbm package.

Ridgeway, G., 2006. Assessing the effect of race bias in post-traffic stop outcomes using propensity scores. Journal of Quantitative Criminology 22, 1–29. https://doi.org/10.1007/s10940-005-9000-9

Ridgeway, G., Mccaffrey, D., Morral, A., Burgette, L., Griffin, B.A., 2017. Toolkit for weighting and analysis of nonequivalent groups: A tutorial for the twang package. Rand 1–30.

Rödiger, M., Hamm, U., 2015. How are organic food prices affecting consumer behaviour? A review. Food Quality and Preference 43, 10–20. https://doi.org/10.1016/j.foodqual.2015.02.002

Rogissart, L., Foucherot, C., Bellassen, V., 2019. Food policies and climate: a literature review. I4CE, Paris, France.

Röös, E., Karlsson, H., Witthöft, C., Sundberg, C., 2015. Evaluating the sustainability of diets-combining environmental and nutritional aspects. Environmental Science and Policy 47, 157–166. https://doi.org/10.1016/j.envsci.2014.12.001

Rosenbaum, P.R., 2002. Sensitivity to Hidden Bias, in: Observational Studies. Springer Series in Statistics, pp. 105–170. https://doi.org/10.1007/978-1-4757-3692-2_4

Rosenbaum, P.R., Rubin, D.B., 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70, 41–55. https://doi.org/10.1093/biomet/70.1.41

Rubin D. B, 1974. Estimating causal effects of treatment in randomized and nonrandomized studies. Journal of Educational Psychology 66, 688–701.

Salou, T., Le Mouël, C., van der Werf, H.M.G., 2017a. Environmental impacts of dairy system intensification: the functional unit matters! Journal of Cleaner Production 140, 445–454. https://doi.org/10.1016/j.jclepro.2016.05.019

Salou, T., van der Werf, H.M.G., Levert, F., Forslund, A., Hercule, J., Le Mouël, C., 2017b. Could EU dairy quota removal favour some dairy production systems over others? The case of French dairy production systems. Agricultural Systems 153, 1–10. https://doi.org/10.1016/j.agsy.2017.01.004

Sanders, J., Gambelli, D., Lernoud, J., Orsini, S., Padel, S., Stolze, M., Willer, H., Zanoli, R., 2016. Distribution of the added value of the organic food chain (No. Ref. Ares(2016)6662331). European Commission.

Schader, C., Jud, K., Meier, M.S., Kuhn, T., Oehen, B., Gattinger, A., 2014. Quantification of the effectiveness of greenhouse gas mitigation measures in Swiss organic milk production using a life cycle assessment approach. Journal of Cleaner Production 73, 227–235. https://doi.org/10.1016/j.jclepro.2013.11.077

Schmidt, J.H., Weidema, B.P., Brandão, M., 2015. A framework for modelling indirect land use changes in Life Cycle Assessment. Journal of Cleaner Production 99, 230–238. https://doi.org/10.1016/j.jclepro.2015.03.013

Schröck, R., 2012. The Organic Milk Market in Germany Is Maturing: A Demand System Analysis of Organic and Conventional Fresh Milk Segmented by Consumer Groups: DEMAND SYSTEM ANALYSIS OF ORGANIC AND CONVENTIONAL FRESH MILK. Agribusiness 28, 274–292. https://doi.org/10.1002/agr.21298

Searchinger, T.D., Wirsenius, S., Beringer, T., Dumas, P., 2018. Assessing the efficiency of changes in land use for mitigating climate change. Nature. https://doi.org/10.1038/s41586-018-0757-z

Seconda, L., Baudry, J., Allès, B., Boizot-Szantai, C., Soler, L.-G., Galan, P., Hercberg, S., Langevin, B., Lairon, D., Pointereau, P., Kesse-Guyot, E., 2018. Comparing nutritional, economic, and environmental performances of diets according to their levels of greenhouse gas emissions. Climatic Change 148, 155–172. https://doi.org/10.1007/s10584-018-2195-1

Seufert, V., Ramankutty, N., Foley, J.A., 2012. Comparing the yields of organic and conventional agriculture. Nature 2–7. https://doi.org/10.1038/nature11069

Shonkwiler, J.S., Yen, S.T., 1999. Two-Step Estimation of a Censored System of Equations. American Journal of Agricultural Economics 81, 972–982. https://doi.org/10.2307/1244339

Silverman, B.W., 1981. Using Kernel Density Estimates to Investigate Multimodality. Journal of the Royal Statistical Society. Series B: Methodological 43, 97–99.

Smith, L.G., Kirk, G.J.D., Jones, P.J., Williams, A.G., 2019. The greenhouse gas impacts of converting food production in England and Wales to organic methods. Nature Communications 1–10. https://doi.org/10.1038/s41467-019-12622-7

Smith, P., 2014. Do grasslands act as a perpetual sink for carbon? Global Change Biology 20, 2708–2711. https://doi.org/10.1111/gcb.12561

Soussana, J.F., Tallec, T., Blanfort, V., 2010. Mitigating the greenhouse gas balance of ruminant production systems through carbon sequestration in grasslands. Animal 4, 334–350. https://doi.org/10.1017/S1751731109990784

Steinfeld, H., Gerber, P., Wassenaar, T., Castel, V., Rosales, M., de Haan, C., 2006. Livestock's long shadow - environmental issues and options. FAO 5, 7. https://doi.org/10.1890/1540-9295(2007)5[4:D]2.0.CO;2

Stonehouse, D.P., Clark, E.A., Ogini, Y.A., 2001. Organic and conventional dairy farm comparisons in Ontario Canada. Biological Agriculture and Horticulture 19, 115–125. https://doi.org/10.1080/01448765.2001.9754916

Sun, B., Morwitz, V.G., 2010. Stated intentions and purchase behavior: A unified model. International Journal of Research in Marketing 27, 356–366. https://doi.org/10.1016/j.ijresmar.2010.06.001

Taheripour, F., Cui, H., Tyner, W.E., 2017. An Exploration of Agricultural Land Use Change at Intensive and Extensive Margins: Implications for Biofuel-Induced Land Use Change Modeling, in: Qin, Z., Mishra, U., Hastings, A. (Eds.), Geophysical Monograph Series. John Wiley & Sons, Inc., Hoboken, NJ, USA, pp. 19–37. https://doi.org/10.1002/9781119297376.ch2

Thomassen, M.A., Dolman, M.A., van Calker, K.J., de Boer, I.J.M., 2009. Relating life cycle assessment indicators to gross value added for Dutch dairy farms. Ecological Economics 68, 2278–2284. https://doi.org/10.1016/j.ecolecon.2009.02.011

Thomassen, M.A., van Calker, K.J., Smits, M.C.J., Iepema, G.L., de Boer, I.J.M., 2008. Life cycle assessment of conventional and organic milk production in the Netherlands. Agricultural Systems 96, 95–107. https://doi.org/10.1016/j.agsy.2007.06.001

Train, K.E., 2003. Discrete choice methods with simulation. Cambridge University Press 9780521816, 1–334. https://doi.org/10.1017/CBO9780511753930

Treu, H., Nordborg, M., Cederberg, C., Heuer, T., Claupein, E., Hoffmann, H., Berndes, G., 2017. Carbon footprints and land use of conventional and organic diets in Germany. Journal of Cleaner Production 161, 127–142. https://doi.org/10.1016/j.jclepro.2017.05.041

Tukker, A., Goldbohm, R.A., De Koning, A., Verheijden, M., Kleijn, R., Wolf, O., Pérez-Domínguez, I., Rueda-Cantuche, J.M., 2011. Environmental impacts of changes to healthier diets in Europe. Ecological Economics 70, 1776–1788. https://doi.org/10.1016/j.ecolecon.2011.05.001

Tuomisto, H.L., Hodge, I.D., Riordan, P., Macdonald, D.W., 2012. Does organic farming reduce environmental impacts? – A meta-analysis of European research. Journal of Environmental Management 112, 309–320. https://doi.org/10.1016/j.jenvman.2012.08.018

Valin, H., Sands, R.D., van der Mensbrugghe, D., Nelson, G.C., Ahammad, H., Blanc, E., Bodirsky, B., Fujimori, S., Hasegawa, T., Havlik, P., Heyhoe, E., Kyle, P., Mason-D'Croz, D., Paltsev, S., Rolinski, S., Tabeau, A., van Meijl, H., von Lampe, M., Willenbockel, D., 2014. The future of food demand: Understanding differences in global economic models. Agricultural Economics (United Kingdom) 45, 51–67. https://doi.org/10.1111/agec.12089

van der Werf, H.M.G., Kanyarushoki, C., Corson, M.S., 2009. An operational method for the evaluation of resource use and environmental impacts of dairy farms by life cycle assessment. Journal of Environmental Management 90, 3643–3652. https://doi.org/10.1016/j.jenvman.2009.07.003

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, 2427–2439. https://doi.org/10.3168/jds.2013-7648

Vertès, F., Mary, B., 2007. Modelling the long term SOM dynamics in fodder rotations with a variable part of grassland. Agronomie 2007–2007.

Wei, T., Simko, V., 2017. R package "corrplot": Visualization of a Correlation Matrix.

Weidema, B.P., Wesnaes, M., Hermansen, J., Kristensen, I., Halberg, N., 2008. Environmental improvement potentials of meat and dairy products, SciencesNew York. https://doi.org/10.2791/38863

Wickham, H., 2016. ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag New York.

Williams, A.G., Audsley, E., Sandars, D.L., 2006. Determining the environmental burdens and resource use in the production of agricultural and horticultural commoditites. Main report. Main Report. Defra Research Project IS0205. Bedford: Cranfield University and Defra. Available on www.silsoe.cranfield.ac.uk, and www.defra.gov.uk 97 pp.

Wirsenius, S., Hedenus, F., Mohlin, K., 2011. Greenhouse gas taxes on animal food products: Rationale, tax scheme and climate mitigation effects. Climatic Change 108, 159–184. https://doi.org/10.1007/s10584-010-9971-x

Yen, S., Kan, K., Su, S.-J., 2002. Household demand for fats and oils: two-step estimation of a censored demand system. Appl. Econ. 34, 1799–1806. https://doi.org/10.1080/00036840210125008

Yen, S.T., Lin, B.-H., Smallwood, D.M., 2003. Quasi- and Simulated-Likelihood Approaches to Censored Demand Systems: Food Consumption by Food Stamp Recipients in the United States. American Journal of Agricultural Economics 85, 458–478. https://doi.org/10.1111/1467-8276.00134

Yiridoe, E.K., Bonti-Ankomah, S., Martin, R.C., 2005. Comparison of consumer perceptions and preference toward organic versus conventionally produced foods: A review and update of the literature. Renew. Agric. Food Syst. 20, 193–205. https://doi.org/10.1079/RAF2005113

Zehetmeier, M., Baudracco, J., Hoffmann, H., Heißenhuber, A., 2012. Does increasing milk yield per cow reduce greenhouse gas emissions? A system approach. Animal 6, 154–166. https://doi.org/10.1017/S1751731111001467

Zhang, F., Huang, C.L., Lin, B.-H., Epperson, J.E., Houston, J.E., 2011. National Demand for Fresh Organic and Conventional Vegetables: Scanner Data Evidence. Journal of Food Products Marketing 17, 441–458. https://doi.org/10.1080/10454446.2011.583190

Zhen, C., Finkelstein, E.A., Nonnemaker, J.M., Karns, S.A., Todd, J.E., 2014. Predicting the effects of sugar-sweetened beverage taxes on food and beverage demand in a large demand system. American Journal of Agricultural Economics 96, 1–25. https://doi.org/10.1093/ajae/aat049

Zhen, C., Muth, M., Okrent, A., Karns, S., Brown, D., Siegel, P., 2019. Do differences in reported expenditures between household scanner data and expenditure surveys matter in health policy research? Health Economics (United Kingdom) 28, 782–800. https://doi.org/10.1002/hec.3883