LIFT

Low-Input Farming and Territories – Integrating knowledge for improving ecosystem based farming

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Farm technical-economic performance depending on the degree of ecological approaches

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About the LIFT research project

Ecological approaches to farming practices are gaining interest across Europe. As this interest grows there is a pressing need to assess the potential contributions these practices may make, the contexts in which they function and their attractiveness to farmers as potential adopters. In particular, ecological agriculture must be assessed against the aim of promoting the improved performance and sustainability of farms, rural environment, rural societies and economies, together.

The overall goal of LIFT is to identify the potential benefits of the adoption of ecological farming in the European Union (EU) and to understand how socio-economic and policy factors impact the adoption, performance and sustainability of ecological farming at various scales, from the level of the single farm to that of a territory.

To meet this goal, LIFT will assess the determinants of adoption of ecological approaches, and evaluate the performance and overall sustainability of these approaches in comparison to more conventional agriculture across a range of farm systems and geographic scales. LIFT will also develop new private arrangements and policy instruments that could improve the adoption and subsequent performance and sustainability of the rural nexus. For this, LIFT will suggest an innovative framework for multi-scale sustainability assessment aimed at identifying critical paths toward the adoption of ecological approaches to enhance public goods and ecosystem services delivery. This will be achieved through the integration of transdisciplinary scientific knowledge and stakeholder expertise to co-develop innovative decision-support tools.

The project will inform and support EU priorities relating to agriculture and the environment in order to promote the performance and sustainability of the combined rural system. At least 30 case studies will be performed in order to reflect the enormous variety in the socio-economic and bio-physical conditions for agriculture across the EU.

Project consortium

No.	Participant organisation name	Country
1	**INRAE - Institut National de Recherche pour l'Agriculture, l'Alimentation et l'Environnement**	**FR**
2	VetAgro Sup – Institut d'enseignement supérieur et de recherche en alimentation, santé animale, sciences agronomiques et de l'environnement	FR
3	SRUC – Scotland's Rural College	UK
4	Teagasc – Agriculture and Food Development Authority	IE
5	KU Leuven – Katholieke Universiteit Leuven	BE
6	SLU – Sveriges Lantbruksuniversitet	SE
7	UNIBO – Alma Mater Studiorum – Universita di Bologna	IT
8	BOKU – Universitaet fuer Bodenkultur Wien	AT
9	UBO – Rheinische Friedrich-Wilhelms – Universitat Bonn	DE
10	JRC – Joint Research Centre – European Commission	BE
11	IAE-AR – Institute of Agricultural Economics	RO
12	MTA KRTK – Magyar Tudományos Akadémia Közgazdaság – és Regionális Tudományi Kutatóközpont	HU
13	IRWiR PAN – Instytut Rozwoju Wsi i Rolnictwa Polskiej Akademii Nauk	PL
14	DEMETER – Hellinikos Georgikos Organismos – DIMITRA	GR
15	UNIKENT – University of Kent	UK
16	IT – INRAE Transfert S.A.	FR
17	ECOZEPT Deutschland	DE

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List of acronyms and abbreviations

AECM: agri-environmental and climate measures

AES: agri-environmental schemes

AIC: Akaike Information Criteria

ANOVA one-way analysis of variance

ATT: Average Treatment Effect on the Treated

AWU: annual working units

AWI: animal welfare index

CAP: Common Agricultural Policy

CDI: crop diversity index

CF: cash flow

COP: cereal, oilseed and protein crops

CRS: constant returns to scale

CS: case study

CV: coefficient of variation

DEA: Data Envelopment Analysis

DMU: decision making unit

DRS: decreasing returns to scale

EC: efficiency change

ESU: economic size unit

EU: European Union

FADN: Farm Accountancy Data Network

FTE: full time equivalent

GDP: gross domestic product

GHG: greenhouse gas

GM: gross margin

GPM: gross profit margin

GRA: growth rate of assets

GWP: global warming potential

ha: hectare

HI: Herfindahl index

IRS: increasing returns to scale

LCA: Life Cycle Assessment

LCM: Latent Class Model

LCSFA: Latent Class Stochastic Frontier Analysis

LCSFM: Latent Class Stochastic Frontier Model

LFA: less favoured area

LSU: livestock unit

MFA: main forage area

MTR: metatechnology ratio

OLS: Ordinary Least Squares

RMEC: residual mix efficiency change

ROA: return on assets

RPM: Random Parameter Model

RPSFA: Random Parameter Stochastic Frontier Analysis

SE: scale efficiency

SEC: scale efficiency change

SFA: Stochastic Frontier Analysis

TE: technical efficiency

TEC: technical efficiency change

TF: type of farming

TFP: total factor productivity

TGR technology gap ratio

TSG: traditional speciality guaranteed

UAA: utilised agricultural area

VRS: variable returns to scale

WP: workpackage

1 Summary

This document presents the results of Task 3.2 (farm technical-economic performance) in workpackage (WP) 3 (farm performance of ecological agriculture) of the LIFT project. The overall aim of Task 3.2 is to assess and compare technical-economic farm performance across the European Union (EU) depending on the degree of ecological approaches adopted by farms and analyse drivers, affecting their performance. This requires an approach, which allows to consider regional specifics, while still allowing comparisons between different regions and countries. The deliverable thus consists of several academic papers, focussing on a range of different case studies, applying a wide range of methods, which can most generally be divided into empirical econometric approaches and bio-economic models. At the same time, all case studies follow a similar structure and include some common elements in terms of the applied methods, in particular a set of common indicators of technical-economic farm performance was implemented in several papers. Various approaches to differentiate farms according to the degree of ecological approaches adopted were explored, including the LIFT farm typology developed in WP1 and other strategies. Overall, our results show that the wide variety of farm types and biophysical, socio-economic and political framework conditions present in the EU matter: results of comparing technical-economic farm performance depending on the degree of ecological approaches adopted, as well as with respect to drivers of farm technical-economic performance, are heterogenous and vary between the different analyses. Therefore, this heterogeneity needs to be considered by policy makers and can most likely best be addressed by providing a policy framework, which provides the necessary flexibility to adjust measures to region-specific framework conditions in order to foster economic viability of farms in the context of an ecological transition of EU agriculture. Building on the results of this deliverable and the other deliverables within WP3, Task 5.1 will in a next step undertake an integrative assessment of all performance dimensions jointly (technical-economic, environmental and private-social performance as well as employment effects at the farm level), uncovering associated trade-offs and synergies of an increasing uptake of ecological approaches in the EU farming sector, while WP6, in particular Task 6.2 and Task 6.3, will further investigate the role of policies in the development of ecological agriculture.

2 Introduction

This document presents the results of studies carried out in Task 3.2 (farm technical-economic performance) in WP3 (farm performance of ecological agriculture) by LIFT partners, and has been edited by Niedermayr A., Kantelhardt J., Eckart L., Kohrs M., Schaller L. and Walder P. (BOKU) who have also written the summary, introduction and conclusion[1].

In the context of the Green Deal and the accompanying strategies like the Biodiversity strategy and the Farm to Fork Strategy, the EU is striving to achieve an increasing uptake of ecological approaches in its farming sector. In this context a crucial question is, how this affects the economic viability of and production of food, feed and fibre by farms within the EU, as these two aspects are also central aims of its Common Agricultural Policy (CAP). Also, the question arises, whether certain framework conditions, which can be influenced by policies, could support this process by, e.g. compensating farmers for possible negative economic effects when adopting ecological approaches or by helping them to

[1] We want to point out that each academic paper of LIFT partners is self contained. Therefore, in each academic paper (sections 3.1 to 5.4), the numbering of tables starts over from Table 1, and the references used in the paper are listed in a reference sub-section in the respective paper. By contrast, the references used in chapters 1 (summary), 2 (introduction) and 6 (discussion) are listed in chapter 9 of this deliverable.

find successful win-win strategies, allowing them to maintain or even increase their economic performance in the course of an ecological transition.

Against this background, the overall **aim of Task 3.2** is to assess and compare technical-economic farm performance across the EU depending on the degree of ecological approaches[2] adopted by farms and analyse drivers, affecting their performance. In order to accomplish this, the wide variety of farm types and biophysical, socio-economic and political framework conditions present in the EU, need to be considered. This requires an approach, which allows to consider regional specifics, while still allowing comparisons between different regions and countries.

The deliverable thus consists of **23 separate academic papers**, focussing on a range of different case studies. However, at the same time, all case studies follow a **similar structure** and share some **common elements** in terms of the applied methods, in particular a set of common indicators of technical-economic farm performance was implemented in several papers. An overview of all papers in this deliverable 3.1 is given in Table 1.

The analyses cover a wide range of **farm types** such as specialist dairy farms, specialist cattle farms, specialist sheep farms, granivore farms, specialist field crop farms, including also specialist cereal oilseed and protein crop farms, specialist olive farms, among others.

In terms of the identification of the **degree of ecological approaches** adopted by farms, the analyses explored a wide range of approaches. Several papers applied the LIFT farm typology protocols, developed in WP1 (Rega et al., 2019; Rega et al., 2021; Thompson et al., 2021), while others identified other nomenclatures, input indicators, key farming practices or farming systems (proxied by combinations of farming practices), better suited for their particular analyses.

Apart from **academic papers of individual LIFT partners** in their respective case study regions, **some collaborative analyses** were also developed, resulting in cross-country papers, identifying and analysing heterogenous production technologies across the French, Irish and Austrian dairy sector using stochastic frontier (section 3.1) estimated with an R-package that was developed within LIFT (Dakpo et al., 2021), and another paper investigating the impact of key policy measures affecting legume production on the uptake of legume production by farms in Germany and France with the bio-economic model FarmDyn (Britz et al., 2019) (section 5.4).

The deliverable is structured into **three main parts**:

- The first part (chapter 3) consists of **empirical analyses of technical-economic farm performance**.
- The second part (chapter 4) contains **empirical analyses, which additionally to technical-economic farm performance also address Deliverable 3.3** (Van Ruymbeke et al., 2021) (farm environmental performance according to the degree of ecological approaches).
- The third part (chapter 5) includes papers which are based on **bio-economic models**, which again in most cases go beyond purely technical-economic farm performance.

In chapters 3 and 4, analyses are mostly carried out with econometric methods. The data sources used range from secondary data like EU/national Farm Accountancy Data Network (FADN) data or national

[2] Ecological practices are understood in LIFT as low-input practices and/or practices that are environmentally friendly. The originality of LIFT in this view is not to focus on a specific type of ecological approaches, but to cover the whole continuum of farming approaches, from the most conventional to the most ecological, including the widest range of ecological approaches. This comprises the existing nomenclatures such as organic farming, low-input farming, agroecological farming, etc. It also encompasses approaches that are not yet part of a nomenclature, but that can be identified with various criteria such as management practices, on-farm diversification etc. Thus, conventional practices mean non-ecological practices.

farm surveys to primary data obtained from the LIFT large-scale farmer survey (Tzouramani et al., 2019) in the respective case study regions. In particular FADN data is very well suited for analyses in this context, as it is based on a representative sample of commercial EU farms and provides harmonised economic data.

In general, each individual paper mostly focussed on one main method to assess farm performance. These **main methods** included methods of **total factor productivity (TFP) and technical efficiency analysis** such as **Data Envelopment Analysis (DEA), Stochastic Frontier Analysis (SFA), Latent Class Stochastic Frontier Analysis (LCSFA)** or **Random Parameter Stochastic Frontier Analysis (RPSFA)**. More background information on these methods can be found in the respective papers in this deliverable and the underlying literature (e.g. Coelli et al., 2005; Greene, 2005; Orea and Kumbhakar, 2004).

Additionally, in most studies, various further indicators of farm technical-economic performance were calculated. In order to provide some common framework for these indicators, a set of **common indicators of technical-economic farm performance** was developed within Task 3.2, based on the previous work in Milestone 17 (Walder et al., 2019) and Milestone 18 (Schaller et al., 2020). The indicators mostly cover profitability, productivity and financial stability. In terms of **profitability**, these indicators allow for example to explore the effect of **opportunity costs** of production factors and the **contributions of public payments and subsidies** to profitability. In terms of productivity, **partial quantitative productivity indicators**, suitable to visualize differences in productivity associated with individual inputs in the production process were used. In some papers, additional indicators to those mentioned above were developed and applied as well.

Depending on the aim of and data available for the respective analysis, different **methods to compare performance according to the degree of ecological approaches** adopted by farms were used. In particular with small datasets, based on data from the LIFT large-scale farmer survey, simple parametric or non-parametric tests were used like **t-test, ANOVA, Mann-Whitney U test, or Wilcoxon test**. However, in several papers, further methods, such as **matching** and **metafrontiers of production possibilities** were explored, enhancing such comparisons by addressing possible biases and improving the identification of **performance gaps**.

A final central aspect of most papers was the assessment **of drivers of performance levels and performance gaps with econometric methods**. The analysed drivers comprise endogenous drivers such as farmers’ age, gender, education, succession status or various indicators of farm structure, and exogenous drivers, like for example agronomic and economic conditions.

While the analyses in the first two parts use observational data of farms to derive inferences, based on what happened in the past, the **bio-economic models** developed and applied in the third part of this deliverable’s empirical analyses, model farms in a bottom-up approach. The advantage of such models is that they can be used to answer various ‘what if’ questions and to provide a detailed assessment of on-farm mechanisms of the adoption of a higher degree of ecological approaches through the implementation of **scenarios**. For example, the models consider **economic and legislative context** (e.g. nitrate directive) and **other boundary conditions** (e.g. farm-plot-distance and plot size, different biophysical site conditions). Additionally, one paper based on bio-economic modelling explored the common indicators of technical-economic farm performance described above as well as a wide range of environmental and labour performance indicators to modelled arable and dairy farms in order to assess the impact of agri-environmental and climate measures on sustainable farm performance.

The further structure of the deliverable is as follows: the next chapter presents the academic papers dedicated to empirical analyses of technical-economic farm performance, chapter 4 contains the academic papers based on empirical analyses, which address this Deliverable 3.1 (farm technical-economic performance) and Deliverable 3.3 (farm environmental performance) simultaneously, and chapter 5 shows academic papers based on bio-economic models, which again in most cases go beyond purely technical-economic farm performance. Finally, after these sections, chapter 6 provides concluding remarks.

Table 1: Overview of academic papers, implemented in the Deliverable

Chapter	Paper	LIFT partner	Case study region	Farm types	Degree of ecological approaches of farms	Methodological approach	Short summary of main findings
	Empirical analyses of technical-economic farm performance						
3.1	Technical efficiency of intensive and extensive technology in dairy farming in the European Union	INRAE, Teagasc, BOKU	France, Ireland, Austria	Specialist dairy farms	Extensive and intensive groups, based on LCSFM	LCSFM, integrating an assessment of drivers of farm performance.	Intensive and extensive production technologies can be identified with easily measurable separating variables in the LCSFM. Extensive farms perform worse compared to intensive farms and subsidies negatively affect performance for extensive farms and have no effect on intensive farms.
3.2	Identifying heterogeneous technologies in Irish dairy farming	Teagasc	Ireland	Specialist dairy farms	Extensive and intensive groups, based on LCSFM	LCSFM, integrating an assessment of drivers of farm performance, calculation of various additional performance indicators (e.g. profitability, productivity).	Intensive farms are more efficient than extensive farms. Additional indicators also show better performance of intensive farms.
3.3	Modelling heterogeneous technologies in the presence of sample selection: The case of dairy farms and the adoption of agri-environmental schemes in France	INRAE	France	Specialist dairy farms	Farm with agri-environmental schemes and farms without, both further divided in an intensive and extensive group, based on LCSFM	Sample selection model and LCSFM, integrating an assessment of drivers of farm performance.	Results show technological heterogeneity of farms. Intensive dairy farms are more efficient. Operational subsidies increase efficiency for intensive farms and decrease it for extensive farms.
3.4	The economic performance of transitional and non-transitional organic dairy farms: A panel data econometric approach in Brittany	INRAE	Brittany	Specialist dairy farms	Conventional corn and grassland systems, organic	Calculation of various economic and financial performance indicators; linear mixed effects model.	Organic farms show on average better economic and financial performance than the other systems, but this requires a certain minimum farm size.

3.5	Investments, ecological approaches, environmental subsidies and the productivity of Italian farms	UNIBO	Italy (differentiated by various regions)	All farm types	Conventional, low input, integrated, organic, low input + integrated, low input + organic, organic + integrated, low input + organic + integrated	Estimation of Levinsohn and Petrin TFP; investigation of correlational relationship to capture the effects of private investment and environmental subsidies and further controls on TFP; calculation of additional partial productivity indicators.	Shifting from conventional to more ecologically-sound type of farming exhibits trade-offs in terms of reduction in productivity, both total and partial. These trade-offs can, however, can be mitigated by investments. Compared to previous studies, results support the positive relationship between environmental subsidies and farms' TFP and average product of land.
3.6	Technical and economic performance of arable farms in Sweden: does the degree of ecological approaches matter?	SLU	Sweden	Specialist field crop farms	Crop diversity index, organic farming, crop rotation	SFA, integrating an assessment of drivers of farm performance (subsidies, crop diversity index, organic farming, crop rotation, policy shock), calculation of various additional performance indicators (e.g. profitability, productivity).	Farms in southern Sweden are more efficient than those in the north. Subsidies positively affect efficiency, while results for ecological approaches are mixed. For most additional performance indicators, conventional farms perform better than organic farms.
3.7	Comparison of total factor productivity and its components between Low input and conventional farming systems: the case of Hungarian Cereal Oilseed and Protein (COP) crop producing farms (2011-2015)	MTA KRTK	Hungary	Specialist cereal, oilseed and protein crop farms	Conventional, low input	RPSFM, allowing for heterogenous production technologies; Törnquist-Theil TFP index.	TFP is smaller for low input farms. Technological change is similar for both groups, but technical and scale efficiency is lower for low input farms.
3.8	Differences in efficiency and productivity between conventional and organic farms: the case of Hungarian cereal oilseed and protein (COP) crop producing farms (2010-2015)	MTA KRTK	Hungary	Specialist cereal, oilseed and protein crop farms	Conventional, organic	RPSFM, allowing for heterogenous production technologies and including an econometric assessment of drivers of farm performance; Törnquist-Theil TFP index; matching; calculation	No significant differences in performance between conventional and organic farms, but low number of organic farms in sample is a limitation.

						of various additional performance indicators (e.g. profitability, productivity).	
3.9	Farm technical and economic performance depending on the degree of ecological approaches: The case of olive farms in Crete, Greece	DEMETER	Crete	Specialist olive farms	Conventional, low input, organic	DEA + second stage regression analysis of drivers of farm performance; calculation of various additional performance indicators (e.g. profitability, productivity).	A transition to ecological practices (low input) can improve farm efficiency.
3.10	Dynamics of productivity and efficiency performance in Poland's dairy farms: comparative analysis by different degrees of ecological approaches	IRWiR PAN	Poland	Specialist dairy farms	Conventional, integrated, low input-integrated, mixed, changeables	DEA + Färe-Primont productivity change index; metafrontier of production possibilities; calculation of various additional performance indicators (e.g. profitability, productivity).	Farms adopting ecological approaches tend to decrease over time. TFP increases over time for conventional, integrated and changeable farms, but decreased for low-input-integrated and mixed farms.
3.11	Productivity and efficiency of pig and poultry farms differentiated by degrees of ecological approaches: the case of Poland	IRWiR PAN	Poland	Specialist granivore farms	Conventional, integrated, changeables	DEA + Färe-Primont productivity change index; metafrontier of production possibilities; calculation of various additional performance indicators (e.g. profitability, productivity).	Farms adopting ecological approaches tend to decrease over time. TFP increases over time for changeable and conventional farms, while it decreased for integrated farms.
3.12	Innovation and eco-system based drivers of total farm factor productivity: assessment based on LIFT large-scale survey (with emphasis on dairy and granivore sectors in Poland)	IRWiR PAN	Poland	Field crop, horticulture, granivore, dairy and mixed farms	-	Identification of drivers (adoption of sources of innovation and ecosystem services), which are hypothesised to influence TFP of farms and comparison of the adoption of these drivers by farm types.	8 indicators, describing sources of information and 24 indicators, describing provision of ecosystem services were identified. Adoption of these indicators varies by farm type.
3.13	Environmentally-friendly practices and economic performance in dairy and	INRAE	Brittany, Sarthe, Puy-de-Dôme	Specialist dairy and beef cattle farms	5 typologies to define ecological farms: usage of antibiotics only	Calculation of various performance indicators (e.g. profitability, productivity); t-tests and matching.	Heterogenous results, when comparing performance of the different ecological and non ecological farm types. It is important to take into account the different

	beef cattle farming in France				for treatment, agroforestry, agri-environment schemes, conversion to organic, organic,		structure of ecological and non-ecological farms when comparing their performance
3.14	Technical-economic performance of ecological farm types for matched cattle and sheep farms in Scotland	SRUC	Scotland	Cattle farms and sheep farms	Low input, high input, low integration, high integration, organic	Slack-based DEA + second stage analysis of drivers of farm performance; Wilcoxon test, matching; calculation of various additional performance indicators (e.g. profitability, productivity).	The development of low-input livestock farms could be beneficial from an economic and narrow environmental perspective. Lower input farms appear to be more efficient and given their low-input nature are also likely to have lower greenhouse gas (GHG) emissions. The benefits of the development of integrated livestock farms is less clear. Organic farms are associated with high levels of efficiency even in the highly-integrated sample so at least relatively the organic price premium, or links to organic associations helped to improve efficiency.
	Empirical analyses of technical-economic and environmental farm performance						
4.1	Pesticide efficiency of French wheat producers under a stochastic frontier framework	INRAE	Northeast France (Marne, in particular)	Specialist field crop farms	Pesticide usage	SFA, using pesticide usage as a damage control input.	Pesticide usage can be reduced to some extent without affecting wheat yield. Crop diversification can positively affect impact damage abatement, but only for low levels of pesticide use.
4.2	Technical-economic and environmental farm performance of dairy farms in Austrian case study regions Steyr-Kirchdorf and Salzburg und Umgebung	BOKU	Steyr-Kirchdorf, Salzburg und Umgebung	Specialist dairy farms	Conventional, haymilk, organic, organic haymilk	DEA + second stage regression analysis of drivers of farm performance; calculation of various additional performance indicators (e.g. profitability, productivity, environmental performance	Organic and organic haymilk farms can compensate economic drawbacks compared to conventional farms through higher subsidies as well as market prices for their products and perform better in terms of environmental performance

						indicators); Mann-Whitney U test; Kruskal-Wallis test	
4.3	Technical-economic and environmental performance of Austrian dairy farms	BOKU	Austria	Specialist dairy farms	Conventional, integrated, organic integrated-organic	DEA + second stage regression analysis of drivers of farm performance; matching and meta-frontier of production possibilities; calculation of various additional performance indicators (e.g. profitability, productivity, environmental performance indicators); t-test; ANOVA.	Organic and integrated-organic haymilk farms can compensate economic drawbacks compared to conventional farms mostly through higher subsidies and perform better in terms of environmental performance
4.4	Integrating a crop diversity index to eco-efficiency measurement for cropland farms in Sweden	SLU	Sweden	Crop land farms	Crop diversity	Eco-efficiency with a directional distance function and crop diversity index (CDI) and Herfindahl index (HI) in the model + second-stage regression.	U shape relationship between eco-efficiency and CDI (measured two years ago). Eco-efficiency was higher after 2013 which is the year of CAP reform with mandatory greening.
4.5	Estimating eco-efficiency of the olive farms in Crete, Greece	DEMETER	Crete (Greece)	Olive farms	Organic farming and non organic farming; conservation farming and non-conservation farming	Eco-efficiency with DEA and only environmental inputs are used in the inputs; second-stage regression.	Conservation farms have the lowest eco-efficiency on average. The actual reason for implementing environmentally-friendly farming practices may be farmers' focus on quality products and not on environmental concerns per se. Subsidies reduce eco-efficiency.
	Bioeconomic modelling						
5.1	Development of a bioeconomic model of pasture-based livestock farms	Teagasc	Ireland	Sheep farms	Lowland and hill farms	Bio-economic model, representative for the population of Irish sheep farms, allowing to investigate technical-economic performance (in particular profitability, cost-indicators and indicators of meat production) and environmental performance (in particular carbon footprint and land occupation).	Results highlight the differential performance of hill and lowland production systems, with lowland systems demonstrating higher output and profitability, less reliance on support payments, higher overall farm emissions but lower emissions per unit output.

5.2	Plot sizes and farm-plot distances as driver of economic farm performance along the degree of ecological approaches	UBO	Western Germany	Arable farms, pig fattening farms, dairy farms	Conventional, organic	Bio-economic model, allowing a detailed assessment of the conversion to organic farming on technical-economic performance, considering in particular the effect of varying farm-plot-distance and plot size.	Organic farms are more profitable, but mostly only if subsidies are considered. In particular organic livestock farms have higher labour requirements. Larger plot size and smaller farm-plot distances increase profitability and decrease labour requirements.
5.3	The impact of agri-environmental and climate measures on sustainable farm performance – a German case study analysis	UBO	Western Germany (North-Rhine-Westphalia)	Arable farms, dairy farms	Conventional non agri-environmental and climate measure farms, conventional agri-environmental and climate measure farms	Comparative-static version of the bio-economic model FarmDyn, assessing technical economic, environmental as well as employment performance of farms.	The implementation of agri-environmental and climate measures improves economic and environmental sustainability of farms while slightly reducing labour requirements. However, this also increases dependency on subsidies and decreases production of food, feed and fibre.
5.4	The impact of European policies on the uptake of ecological approaches – legume production on dairy farms challenged by European policy interaction	UBO, INRAE	France (Pays de la Loire), Germany (North-Rhine-Westphalia)	Dairy farms	Greening regulation and various measures supporting for legumes	Comparative-static version of the bio-economic model FarmDyn, investigating the technical-economic and environmental performance of farms under various scenarios regarding voluntary coupled support for legumes and nitrate directive.	Legume production can be increased to some extent already by a low voluntary coupled support, while this does not lead to any substantial environmental benefits based on the investigated indicators.

3 Empirical analyses of technical-economic farm performance

3.1 Technical efficiency of intensive and extensive technology in dairy farming in the European Union (INRAE, BOKU and Teagasc)

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3.1.1 Introduction

Our study illustrates how latent class modelling combined with stochastic frontier analysis can be used to help policy-making for environmental-friendly "extensive" agriculture in the European Union (EU), through: identification of already extensively producing farms at a large spatial scale; comparison of intensive and extensive farms in terms of economic performance to assess the level of trade-offs between economic performance and environmental sustainability; and investigation of agri-political conditions required for extensive farms to be economically successful.

3.1.2 Description of case study region

Our study is applied to dairy farms and to three EU countries, Ireland, France and Austria. Ireland is one of Europe's leading low-cost dairy producers, characterised by very productive grasslands. This has led to the broad adoption of a seasonal production system with compact spring calving so that milk production matches grass growth. Organic dairy production is a niche subsector contributing 11% of national milk supply from 62 organic dairy farms (out of a total of over 18,000) with an average herd size of 79 cows in 2019. This is in comparison to a national population of 16,700 specialist dairy farms (12% of all farms) with an average herd size of 80 cows (Donnellan et al., 2020).

In France there are not many organic dairy farms either. Although France is the second biggest producer of cow milk in the EU, with 17% of the EU milk, behind Germany (23%) (Eurostat, 2021), only 4% of the milk is produced under organic farming practices (certified or in conversion) (Agreste, 2020). Milk is produced in France in three main areas: around half of the national production comes from plain areas in Western France where dairy farms are intensive with a higher use of maize silage; one third is produced by mixed crop and livestock farms in northeastern France, while the rest is produced by farms in the mountains (Guesdon and Perrot, 2010).

Dairy farms in Austria are mainly located in the Alps, where less favourable climatic conditions and topography result in a comparably small average farm size (31 hectares and 39 livestock units). Nevertheless, Austrian dairy farms are highly productive and are characterised by a high share of organic production (25%) and rely on additional income sources such as forestry (Federal Ministry of Agriculture, Regions and Tourism, 2020a). With respect to the adoption of ecological approaches, Austria has the highest share of organic farms in the EU (18.3% in 2017) and the share of organic farms with milk delivery is even higher (25.5% in 2017) (Federal Ministry of Agriculture, Regions and Tourism, 2020b).

3.1.3 Data

We use data from the Farm Accountancy Data Network (FADN), a harmonised database of bookkeeping information for commercial farms across the EU. This article focuses on specialist dairy farms, for which at least two thirds of their standard output is obtained from dairy activity. The sample used contains a total of 4,316 farms, with, for the years 2014 and 2015 respectively: 326 and 324 Irish farms; 1,037 and 1,019 French farms; and 808 and 802 Austrian farms. In this analysis, all monetary values are deflated with real price indices obtained from Eurostat.[3]

Table 1 describes the pooled sample used, as well as the three countries' sub-samples. Dairy farms in the Austrian sub-sample are smaller than Irish and French farms in terms of land area (31 ha of UAA vs. 63 and 102 ha), mainly located in mountainous areas and more than one quarter (28%) are organic farms. Despite their small size in terms of output, Austrian farms have a higher milk yield than Irish farms, and a higher productivity per ha and per livestock unit (LSU) than Irish and French farms. They receive a much higher value of operational subsidies, 623 vs. 308 (France) and 164 (Ireland) Euros per LSU. The operational subsidies considered here are Common Agricultural Policy (CAP) subsidies excluding investment subsidies, and include production direct and coupled subsidies as well as subsidies from AES and compensating subsidies for being located in Less Favoured Areas (LFA). The latter are mountainous areas or areas with natural constraints. The high value of subsidies per hectare in Austria is explained with AES, organic and LFA payments, as well as other second pillar payments, as Austria offers a very broad and well accepted rural development program with high participation rates of farms.

On average dairy farms in the Irish sub-sample have a greater herd size and a higher livestock stocking rate in terms of the number of LSU per ha of forage area than their French and Austrian counterparts. Very few of the Irish sample farms are organic farms, reflecting a national population of less than 30 certified organic dairy farms in the reference period. The Irish farms on average apply more chemical fertilisers per hectare than French and Austrian farms, but much less crop protection products. This is reflected in the grass based production system, with 98% of land area under permanent grassland, and higher stocking rates. The grass based production system aims to maximise low cost grass utilisation and milk solids output per hectare. This is illustrated in Irish farms having the lowest milk yield per cow but the highest total farm output per labour unit, while demonstrating the lowest costs per litre. These farms receive the lowest amount of subsidies per LSU on average, due to low prevalence of organic dairy farms, lower AES payments and the high LSU per hectare.

French dairy farms in the sub-sample have the highest UAA (102 ha) but the lowest capital value on average. This is compensated by the highest cost of external capital through contract work. They use the highest level of intermediate consumption and crop protection products per ha compared to farms

[3] Index price of agricultural goods output, including fruits and vegetables; index price of goods and services currently consumed in agriculture; index price of goods and services contributing to agricultural investment. (https://ec.europa.eu/eurostat/web/main/data/database)

in the Irish and Austrian sub-samples. The French sub-sample's farms have the highest average share of rented area in UAA (85%), one reason being that land operated by farms with associates is often owned by the associates who rent it out to the farm. A lower share of farms in the French sub-sample is located in LFA compared to the Irish and Austrian sub-samples. Only 5% of the French sub-sample are organic farms, in line with the national statistics.

3.1.4 Methodology

We use here the latent class stochastic frontier model (LCSFM) to classify farms into extensive and intensive technologies. The LCSFM allows an endogenous categorisation of farms into classes of more or less intensive farms, represented by different production technologies, while simultaneously estimating the technical efficiency of each class (see for example Orea and Kumbhakar, 2004). Moreover, the probability of adopting a particular technology can be based on separating variables, in our case selected farms' characteristics, and the model also allows to estimate the effects of drivers of inefficiency.

With the R package {sfaR} (Dakpo et al., 2021a), we apply the LCSFM to the whole sample, pooling the three countries and the years. A Cobb-Douglas specification is used for the technology, with total farm output in Euros as the single output and five inputs: UAA in ha, total farm labour in AWU, herd size in LSU, intermediate consumption in Euros, and capital in Euros. Intermediate consumption includes variable inputs used for production, such as animal feed, seeds, pesticides, fertilisers, water, and electricity. Capital is measured here as the value of assets, excluding the value of livestock (since it is already accounted for in the herd size input) and the value of agricultural land (accounted for in UAA input). In the Cobb-Douglas production function, we also include a time dummy (year 2014) and two country dummies to control for country-specific and time-specific effects.

Separating variables for the identification of different production technologies are selected based on the literature on intensive vs. extensive technology in dairy farming (e.g. Kellermann and Salhofer, 2014; Dakpo et al., 2021b), data availability and on technological characteristics relevant in all the three countries studied. Two variables are used in our final model: the stocking density, calculated as the number of LSU per ha of forage area, and the permanent pasture ratio in UAA. Additionally, we also include a time dummy for the year 2014.

As regards inefficiency drivers, they are selected based on the rich existing literature and particularly articles on dairy farms in EU countries (Latruffe et al., 2017; Bradfield et al., 2020). Specifically, we use the ratio of hired labour in total farm labour, the ratio of rented land in UAA, the value of CAP operational subsidies per LSU and two country dummies for Ireland and France.

Table 1: Descriptive statistics of the sample used pooled over the period 2014-2015

	Three countries pooled		Ireland		France		Austria	
Number of observations	4,316		650		2,056		1,610	
Share of farms located in LFA	66%		64%		49%		90%	
Share of farms located above 600m	31%		0%		20%		57%	
Share of fully organic certified farms	13%		0%		5%		28%	
Share of partly organic farms or in conversion	1%		0%		2%		1%	
	Mean	*Std. dev.*	Mean	*Std. dev.*	Mean	*Std. dev.*	Mean	*Std. dev.*
Total farm output (Euros)	164,810	*118,873*	179,373	*108,961*	210,484	*131,931*	100,603	*63,249*
Total farm labour (AWU)	1.94	*0.88*	1.67	*0.7*	2.01	*1.05*	1.95	*0.65*
Herd size (LSU)	89	*66*	129	*72*	115	*63*	39	*23*
Intermediate consumption (Euros)	108,106	*85,331*	109,541	*70,266*	148,434	*94,797*	56,026	*35,573*
Capital excluding herd and agricultural land (Euros)	427,598	*284,177*	444,709	*285,743*	348,101	*256,090*	522,209	*287,622*
Milk yield (litres per dairy cow)	6,517	*1,572*	5,508	*1,036*	6,818	*1,615*	6,540	*1,530*
Total farm output per ha (Euros)	2,778	*1,406*	2,867	*964*	2,162	*933*	3,530	*1,661*
Total farm output per LSU (Euros)	2,063	*866*	1,376	*280*	1,835	*595*	2,630	*973*
Total farm output per AWU (Euros)	86,383	*47,703*	108,027	*48,333*	106,879	*43,723*	51,472	*27,805*
Stocking density (LSU/ha of forage area)	1.64	*0.62*	2.12	*0.57*	1.56	*0.61*	1.55	*0.57*
Ratio of permanent grassland in UAA	0.86	*0.16*	0.98	*0.06*	0.79	*0.16*	0.89	*0.15*
Costs of fertilisers per ha of UAA (Euros)	99	*88*	228	*87*	104	*62*	42	*54*
Costs for crop protection per ha of UAA (Euros)	28	*35*	8	*12*	47	*39*	11	*21*
Operational subsidies per LSU (Euros)	404	*269*	164	*65*	308	*126*	623	*298*
Including AES subsidies per LSU (Euros)	39	*88*	9	*24*	15	*38*	82	*125*
Ratio of hired labour in total labour	0.07	*0.14*	0.11	*0.17*	0.09	*0.16*	0.02	*0.07*
Ratio of rented land in UAA	0.54	*0.38*	0.23	*0.21*	0.83	*0.27*	0.30	*0.25*

Notes: Labour is measured with annual working units (AWU) which are full-time equivalents.

3.1.5 Results

We estimated the model for different numbers of classes. In the final specification we decided to constrain the model to identify only two classes, as this increased the visibility and made the illustration more straightforward.

Table 2 presents the estimation results regarding the separating variables, the production functions, and the inefficiency drivers for a model with two classes. The coefficients for the separating variables show that a higher stocking density increases the probability of belonging to class 1 while the ratio of permanent grassland in total UAA decreases it. Therefore, class 1 contains farms that are more intensive on average in terms of these two indicators, than farms in class 2. We will therefore label class 1 the intensive class and class 2 the extensive class in what follows. Each class makes up about 50% of all farms. Looking at the composition of the classes by country, a higher share of farms from Ireland and Austria are in the extensive class: 56% and 61% respectively, compared to French farms (40%).

For both classes, in the production function the production inputs are significant and have the expected sign, except for UAA. This suggests that land is not a limiting input for both classes, including the intensive class. The intensive class, on average, shows a higher technical efficiency (with mean efficiency 0.937) than the extensive class (with mean efficiency 0.809) (the efficiency means are significantly different at the 1%-level). The intensive class also has higher elasticities of labour and capital inputs, higher milk yields and a higher farm income in comparison to the extensive class, which has in turn higher livestock and variable inputs' elasticities. Additionally, the intensive class is characterised by a higher livestock density, a lower share of permanent grassland, higher usage of chemical inputs and lower AES subsidies per LSU. As underlined by Kellermann and Salhofer (2014), permanent grassland is less productive than silage in terms of energy content, which may partly explain the lower performance of the extensive class compared to the intensive class in the results here. One reason for the lower AES subsidies per LSU of the intensive class may be organic AES, since the extensive class has a higher share of organic farms than the intensive class (16% vs. 10%).

Results also confirm that the three countries have different production systems: while Irish farms demonstrate the highest total farm output per AWU and lower costs of production (Table 1), when all factors of production are taken into account in the efficiency analysis (Table 2), they are shown to be less productive than French and Austrian farms, as indicated by the country dummies. The time dummy shows for both classes that 2014 was a more productive year than 2015.

With respect to drivers of inefficiency, a negative sign reveals a negative impact of the driver on technical inefficiency and thus a positive impact on technical efficiency. Our results indicate that using hired labour increases technical efficiency only in the extensive class, suggesting a positive effect of extensive farming in rural areas and confirming the finding of Bradfield et al. (2020) for Irish dairy farms and Latruffe et al. (2017) for dairy farms in nine EU countries. A higher share of rented land increases technical efficiency for both classes, also in line with Bradfield et al. (2020).

The effect of subsidies per LSU on inefficiency is not significant for the intensive class but positive for the extensive class. This indicates that, in the latter class, farms receiving more subsidies per LSU are less efficient compared to other farms. This is in line with a large part of the literature investigating subsidies (see Minviel and Latruffe, 2017). We estimated the model again but this time disentangling AES subsidies and other subsidies operational subsidies. Results show that there is no change for both classes. For the extensive class, the non-AES subsidies as well as the AES subsidies have a positive sign, that is to say a negative impact on technical efficiency. For the intensive class, AES subsidies and non-AES subsidies have no significant impact.

Table 2: Estimation results: separating variables, production function and inefficiency drivers

		Class 1 (intensive)		Class 2 (extensive)	
		Coefficient	Sign.	Coefficient	Sign.
Separating variables: probability to belong to class 1					
Intercept			1.58988		
Stocking density			0.55197 ***		
Ratio of permanent grassland in UAA			-3.10614 ***		
Dummy 2014			0.30614		
Production function: log(total farm output) as dependent variable					
Intercept		2.90547	***	1.52412	***
log(UAA)		0.00654		0.00881	
log(total farm labour)		0.12369	***	0.05970	***
log(herd size)		0.15966	***	0.27100	***
log(intermediate consumption)		0.54630	***	0.64666	***
log(capital excluding herd and agricultural land)		0.16703	***	0.14797	***
Dummy Ireland		-0.11704	**	-0.14061	***
Dummy France		-0.08214	**	-0.12782	***
Dummy 2014		0.02400	***	0.04150	***
Inefficiency drivers					
Intercept		-2.43007	***	-3.42984	***
Ratio of hired labour to total labour		-0.39056		-0.88254	**
Ratio of rented land to UAA		-1.89161	***	-0.39569	*
Operational subsidies per LSU		-0.00044		0.00120	***
Dummy Ireland		-3.34144		0.10411	
Dummy France		-2.47456	**	0.27463	*
Model's statistics					
Log-likelihood value			1,626.75		
Posterior probability		0.72		0.74	
Efficiency					
Mean		0.937		0.809	
Number of farms					
Number of farms in total including	(% in sample)	2,148	(50%)	2,168	(50%)
Number of Irish farms	(% in Ireland)	288	(44%)	362	(56%)
Number of French farms	(% in France)	1,237	(60%)	819	(40%)
Number of Austrian farms	(% in Austria)	623	(39%)	987	(61%)

Note: Sign. indicates significance at the 10% (*), 5% (**), or 1% (***) level.

3.1.6 Conclusion

This study analysed and compared the technical efficiency of intensive and extensive dairy farms in Ireland, France and Austria, with FADN data from the period 2014-2015. Using a LCSFM and two easy-to-measure variables to identify classes (share of permanent grassland in UAA, stocking density), we were able to identify intensive and extensive farms. The latter farms not only have a lower stocking density and rely more on permanent grassland, they also use fewer chemical pesticides and fertilisers. Thus, this method allows for the identification of thresholds of permanent grassland and stocking rate to define classes of farms depending on their degree of intensive technology. It also enables the identification of performance gaps between classes in terms of technical efficiency, partial productivity indicators, and income. Our results show, extensively producing farms are currently performing worse economically than intensive farms, and while current CAP subsidies received by farmers have no impact on intensive farms, they reduce the technical efficiency of extensive farms.

This has importance for policy design. The CAP greening payment, and in particular the minimum thresholds to receive this greening payment, could be designed using the method used here in order to adequately compensate farmers for losses due to more extensive production practices. In this context, recent research suggests that extensive and intensive production technologies in dairy farming are largely linked to local natural production conditions and public payments, adapted to local site conditions, as well as additional income sources that may be decisive for the successful implementation of an extensification strategy on farms (Renner et al., 2021).

Extensification, which also includes converting to organic farming, may be a successful adaptative strategy in order to increase the resilience of farms with regard to changing economic conditions, namely increased market volatility, end of dairy quotas and COVID-19 crisis (Bouttes et al., 2019; Darnhofer, 2021). However, as our results show, extensively producing farms are currently performing worse economically than intensive farms, thus government support is necessary to compensate for the loss in economic sustainability while increasing environmental sustainability. Policy design should nonetheless also account for the results from the inefficiency drivers: while current CAP subsidies received by farmers have no impact on intensive farms, they reduce the technical efficiency of extensive farms, suggesting that the current type of subsidies is not adequate for extensive technologies.

It should be underlined that the existing FADN data are limited in that they only provide proxies for identifying more environmentally-friendly production technologies. While our analysis shows that such proxies do have the discriminatory capacity to identify intensive and extensive production technologies and can provide helpful insights, in the medium to long run, FADN data should be extended by additional indicators to identify extensive farming systems and their environmental effects more clearly. However, in the quest for such indicators, both costs and benefits need to be weighed (Kelly et al., 2018).

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3.2 Identifying heterogeneous technologies in Irish dairy farming (Teagasc)

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3.2.1 Introduction and description of case study region

The current reform of the Common Agricultural Policy (CAP) of the European Union aims to target environmental challenges such as climate change and biodiversity loss. The current CAP provides agri-environmental schemes and 'green' payments to incentive farmers to use more environmentally friendly practices; for many farmers, this means farming more 'extensively'. However, while extensive farming may not always be clearly defined, it is crucial to be able to identify extensive farms in order to provide targeted supports. This report aims to provide a better understanding of intensive and extensive dairy farming in Ireland.

Ireland is one of the largest milk producers in Europe, with steadily increasing numbers of dairy cows since the abolition of milk quotas in 2015 (Läpple & Sirr, 2019). The Irish dairy sector is export-oriented with exports valued up to 4 billion euros per year since 2017. In 2017, Ireland produced 5% of the EU milk supply, consuming just 6% of total milk produced as fresh milk and exporting the remainder (Kelly et al., 2020). Although Ireland exports dairy products to more than 120 countries in the world, the largest destinations are the United Kingdom, the Netherlands, China, Germany, and the United States (Bord Bia, 2021).

Irish grass-based dairy farms are relatively unique in Europe since most farms operate a seasonal milk production system with compact spring calving so that milk production matches grass growth. In operating this system, the proportion of grazed grass in the diet of dairy animals is optimised as well-managed grass-based systems can be highly productive (Macdonald et al., 2008). Dairy cows graze on pastures for most of the year, from early spring to late autumn, on average 240 days per year out on pasture with 95% of their diet consisting of grass (Bord Bia, 2021).

Benefiting from mild winters and annual rainfall between 800 and 1200 mm allowing grass growth almost all year around, Ireland is also one of Europe's leading low-cost milk producers (Thorne and Fingleton, 2006), which is considered as the main competitive advantage of Irish dairy farming (Läpple et al., 2012; Mihailescu et al., 2015). O'Brien et al. (2018) showed that 60% of the total dry matter diet of dairy cows in Ireland comes from grazed pasture with the remaining 22% from conserved forage and 18% from concentrate feed. Although Irish dairy enterprises are distributed throughout the 26 counties, they tend to be concentrated in the east and south on better quality soils with high productivity and livestock carrying capacity.

Irish dairy farms have been increasing in size and changing production techniques by adopting more intensive farming systems as indicated by an increase in the number of dairy cows per hectare (stocking density), improvements in dairy cows genetics and an increase in the share of concentrates in the diet (Alvarez & del Corral, 2010). Intensive farms use more non-land inputs, which could lead to environmental externalities. Irish dairy production systems are managed intensively compared to other Irish grassland agricultural production systems (Mihailescu et al., 2015). Literature has shown that intensive farms are on average more technically efficient than extensive ones (Dakpo et al., 2021; Buckley et al., 2019). In this report, we aim to analyse the technical efficiency of Irish dairy farms with heterogeneous technologies and assess performance based on economic indicators.

3.2.2 Farm typologies

For the purpose of this analysis across LIFT partner countries, a FADN (Farm Accountancy Data Network) based protocol describes farm typologies in terms of the level of incorporation of ecological approaches into the system of each farm that goes beyond the existing farm typologies (Rega et al., 2021). The FADN-based protocol is based on the calculation of an overall score as the weighted average score of selected variables including stocking density, feed, pest control, energy use, seeds, fertilisation and depreciation. If the overall score is larger than a threshold, the farm is assigned to the assessed farming typology. In this study, the farm typology protocol is applied to 979 Irish dairy farms in the period 2013 to 2015.

According to the FADN-based protocol, low-input farming, integrated farming, organic farming and standard farming are the four main typologies. Low-input farming denotes a farming system in which the overall use of production inputs is relatively lower, compared to the average level of input of similar farms. According to the protocol, Ireland has 82, 156 and 154 low-input dairy farms in 2013, 2014 and 2015, respectively. The increase between 2013 and 2014 is mainly due to the reduction in the use of fertiliser and feed.

Integrated farming denotes the level of internal integration and circularity of the farm as an ecological unit. There are 3, 6 and 7 integrated dairy farms in Ireland in 2013, 2014 and 2015, respectively. The relatively low number of integrated dairy farms in Ireland results from the high stocking density and low provision of own feed. There are 2, 5 and 7 farms classified as both integrated and low-input farms in 2013, 2014 and 2015, respectively. There are only two certified organic dairy farms in the dataset. According to Läpple & Cullinan (2012), there are many reasons for the low number of organic farms including farmers' perceptions of organics, profitability and availability of organic schemes, amongst others. A visualisation of the typology (Figure A1-A3) is included in the appendix of this report.

3.2.3 Methodology

The estimation of production functions is commonly undertaken using the assumption of homogeneous technologies for all producers. However, if farms adopt varied technologies, estimating a single technology for all farms can yield biased estimates of the technological characteristics (Alvarez & del Corral, 2010; Cillero et al., 2019). The most common approach to address the issue of production heterogeneity is to first split the sample into several groups based on *a priori* information and then estimate the technical efficiency for each group based on stochastic frontier models (SFM) (Alvarez & del Corral, 2010). In this paper, we adopt a latent class stochastic frontier model to estimate the efficiency of two different dairy production systems according to the degree of intensification.

A latent class model (LCM) defines a finite number of classes into several groups and estimates the technology for each group in one stage. The advantage of LCM is that imposing *a priori* criteria to identify which producers are in which class is not necessary. A latent class stochastic frontier model (LCSFM) also allows us to examine whether some exogenous variables in the probability function are responsible for identifying various latent classes (Kumbhakar & Tsionas, 2011).

The latent class stochastic frontier model has been well described in the literature (Alvarez & del Corral, 2010, Dakpo et al., 2021). We briefly summarise the model by constructing a latent class stochastic frontier production function as

$$y_{it} = f\left(x_{it|j}\right) * \exp\left(v_{it|j} - u_{it|j}\right)$$

where subscript i denotes farm, t denotes time and j denotes the different classes. y is the output and x is a vector of inputs. The general residual equals to $\varepsilon_{it|j} = v_{it|j} - u_{it|j}$ where u indicates the inefficiency component. We assume that $v_{it|j}$ follows a normal distribution centred at zero and $u_{it|j}$ follows a half-normal distribution.

Technology heterogeneity indicates that sample can be classified into J latent classes. The production function for each class j equals

$$\ln y_{it} = \tau_j + \sum_{k=1}^{K} \alpha_{k|j} \ln x_{kit} + \sum_{t=2013}^{t=2015} \beta_j D_t + \gamma_j R_i + v_{it|j} - u_{it|j}$$

Where τ_j denotes the class-specific intercepts, k denotes the number of inputs, D_t are time dummies, and R_i is the regional dummy. The likelihood function $\left(LF_{it} = \sum_{j=1}^{J} P_{it|j} LF_{it|j} \right)$ for each farm is obtained as a weighted average of its likelihood function for each group j using the prior probabilities of class j as weights. The prior probabilities are based on a multinomial logit estimation with separating variables based on the individual characteristics identifying various latent classes. The posterior probabilities of class membership are estimated based on Bayes theorem. In this study, we allow farms to switch among different latent classes over time.

To quantify gaps in performance of different latent classes, we adopt various profitability and productivity indicators. The private revenue-cost-ratio expresses the ability of a farm to cover costs with its private revenues. The difference between private and public revenue-cost-ratios represents whether subsidies are considered in revenue calculation. We distinguish the revenue-cost-ratio with and without considering the remuneration of owned production factors in the calculation, to compare the profitability of farms irrespective of how they operate (e.g., family labour or paid labour). Partial productivity indicators applied in the report include average product of land, labour, capital, and average product of intermediate consumption.

3.2.4 Data

This study utilises data from FADN, which is the only source of microeconomic data based on harmonised bookkeeping principles in the European Union. The variables used in this study include total milk output (Euros), land area (in utilised agricultural area, UAA, in hectares), total labour (in full time equivalent annual working units, AWU), intermediate consumption (Euros), and capital (Euros). Intermediate consumption includes veterinary expenses, fertilisers and pesticides use, seeds purchase and other variable materials related to animal food consumption. The capital variable excludes the land value[4] and value of livestock. The values of inputs and products are adjusted with deflation indices to the base year value in 2010.

We include year dummies for 2013 and 2014 (2015 as the baseline category), and a region dummy indicating whether the farm is located in Border, Midland, Western (region=1) or the farm is located in the South and East (region=0) where the environmental context e.g. soil quality, facilitates greater

[4] Due to the missing land values in 2013, we approximate land values for each farm in 2013 with the average of land values in 2014 and 2015. We exclude 27 dairy farms that are present in 2013 but not in the later years.

production in general. The separating variables we adopt in this study to classify intensive and extensive dairy farms include stocking density and a regional dummy. Stocking density is a crucial indicator measuring the intensification of a farm. Because physical differences among regions may affect the choice of the technology, we also introduce the region dummy as a separating variable (Kumbhakar et al., 2009). Since the average share of permanent grassland in Ireland is up to 98% with a median of 100%, we do not consider it as an appropriate separating variable. We remove two outliers in the sample because their capital is too high considering other characteristics of the farm. Table 1 shows the descriptive statistics.

Table 1: Descriptive statistics of Irish dairy farms, 2013 - 2015

	Mean	Median	Std. dev.	Min	Max
Output (Euros)	188100	158544	117983	11545	787997
Land (ha)	62.6	54.7	33.4	8.1	255.6
Labour (AWU)	1.7	1.5	0.7	0.2	7.0
Capital (Euros)	392523	323047	286574	15400	2620260
Consumption (Euros)	109511	94175	69277	9538	496630
Stocking density (LU/ha)	2.1	2.1	0.6	0.5	4.4
Number of observations	948				

3.2.5 Results

The sample is divided into two latent classes to analyse the effects of intensification on the technical efficiency of Irish dairy farms. The choice of being classified into one class for each farm in the sample is guided by the value of the average posterior probability. Table 2 shows the estimation results for the production function, inefficiency drivers, and separating variables. The results show that an increase in stocking density increases the probability of being classified as class 1. Therefore, class 1 contains relatively more intensive farms and class 2 is relatively more extensive farms, even though Ireland has a high stocking density in general compared with other European countries. However, the location of farms does not have a significant impact on classification.

There are 663 intensive farms and 285 extensive farms classified by the latent class stochastic frontier model. All inputs in the production function have statistically significant positive impact on the output, except for the input of labour in the extensive class, i.e. labour does not have a significant impact on the output for extensive dairy farms in Ireland. As would be expected, dairy farms located in less favoured areas (LFA) have significantly lower output. The year dummies show that compared with the year 2015, both the year 2013 and 2014 are less productive years. Farms located in southern and eastern regions have significantly higher output.

For the estimation of inefficiency determinants, a negative coefficient indicates a negative impact on the technical inefficiency, i.e. a positive impact on the technical efficiency. We do not see any significant inefficiency determinants for intensive dairy farms while for extensive farms, operational subsidies per ha of UAA and share of rented area in total UAA have a positive effect on the technical efficiency. As mentioned in the literature, the impact of subsidies on farms' technical efficiency is ambiguous (Dakpo et al., 2021). The intensive dairy farms in the sample are on average more technically efficient than the extensive ones.

Table 2: Estimation results for latent class stochastic frontier models

Production function	Class 1	Class 2
Intercept	3.35336***	1.68535***
Log(land)	0.29322***	0.28323***
Log(labour)	0.04645**	-0.0547
Log(capital)	0.08163***	0.05962***
Log(consumption)	0.58076***	0.74295***
LFA	-0.04078***	-0.06865**
D2013	-0.23181***	-0.21716***
D2014	-0.20507***	-0.16470***
Region	0.04594***	0.11573***
Inefficiency determinants		
Intercept	-3.33878***	-2.00385***
Operational subsidies per ha of UAA	-0.00334	-0.00309**
Share of hired labour in total labour	-11.51535	-1.01838
Share of rented area in total UAA	-1.46231	-2.41508***
Separating variables		
Intercept	-10.94487***	
Stocking density	6.24078***	
Region	-0.46259	
Observations	663	285
Average efficiency	0.9521	0.8635
Average posterior probability	0.9187	0.8789

Note: *, **, and *** indicates significance at 10%, 5%, and 1%, respectively.

Table 3 shows the characteristics of both classes of dairy farms in the sample. Intensive dairy farms have on average higher stocking density and higher level for all inputs, except for land. The difference of land in two latent classes is not significantly different. More extensive farms are located in the less favoured areas compared with intensive ones.

We also apply profitability indicators and productivity indicators to farms in each class. On average, intensive dairy farms in the sample have significantly higher profits and productivity indicated by higher private and public revenue-cost-ratio (with/without remuneration), higher average product of land, labour, capital and intermediate consumption. There is no significant difference in equity ratio between two latent classes. Table A1 in the appendix summarises the profitability indicators and productivity indicators for both dairy and beef farms between 2013 and 2015.

Table 3: Comparison of two latent classes

	Mean_C1	Mean_C2	t-test
Output (Euros)	212102	132262	***
Herd size (LU)	140.44	96.33	***
Land (ha)	62.32	63.2	
labour (AWU)	1.722	1.529	***
Capital (Euros)	425619	315532	***
Consumption (Euros)	119642	85942	***
LFA	0.5837	0.7825	***
Region	0.7919	0.7123	**
Operational subsidies per ha of UAA (Euros)	333.65	288.6	***
Share of hired labour in total labour	0.12542	0.07609	***
Share of rented area in total UAA	0.231566	0.2111	**
Stocking density (LU/ha)	2.3396	1.5435	***
Farm net value added/AWU (Euros/AWU)	60668	37097	***
Private revenue-cost-ratio	1.4542	1.2614	***
Public revenue-cost-ratio	1.6135	1.4648	***
Private revenue-cost-ratio (remuneration)⁜	1.0725	0.9127	***
Public revenue-cost-ratio (remuneration)⁜	1.188	1.0493	***
Product land (Euros/ha)	3728	2226	***
Product labour (Euros/AWU)	135378	93570	***
Product capital	0.15379	0.12242	***
Product expense	1.7571	1.4962	***
Equity ratio	0.954	0.9579	

⁜Calculated ratio considering remuneration of owned production factors. Note: *, **, and *** indicates significance at 10%, 5%, and 1%, respectively.

3.2.6 Discussion and conclusions

There have been debates over the future of farming systems focusing heavily on the socio-ecological trade-offs between intensive and extensive pathways for growth (Coomes et al., 2019; Dakpo et al., 2021). Based on the latent class stochastic frontier model, we identify intensive and extensive dairy farms in Ireland and analyse the technical efficiency of both typologies of farms with stocking density and a regional dummy as separating variables. The study confirms that intensive farms are more technically efficient and there exist significant differences in output and across inputs between intensive and extensive farms in the sample. Various economic indicators show that intensive farms are more profitable in general.

The relationship between agriculture and the environment is complex. Recent reforms of the Common Agricultural Policy of the EU are increasingly focused on the environmental impact of intensive agriculture. Our study provides crucial information for future design of the agri-environmental policies to regulate production or to compensate farms that may experience a decrease in productivity and revenue with an extensive farming practice; this is important for enhancing the competitiveness of European farms to compete in the global markets.

A limitation of this study lies in the lack of separating variables (e.g. soil quality) that could capture environmental differences between farming typologies as described using the FADN dataset. Further work is planned to add more agronomic and spatial variables from the Irish National Farm Survey data to further nuance the estimation.

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3.2.8 Appendix

Figure A1-A3. Visualisation of the farm typology, 2013-2015

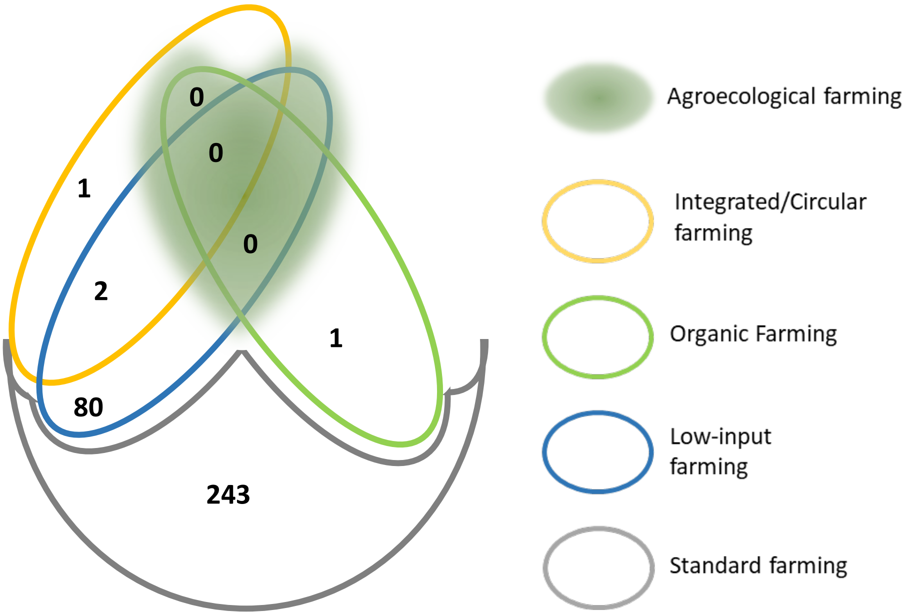

Figure A1. Typology of Irish dairy farms, 2013

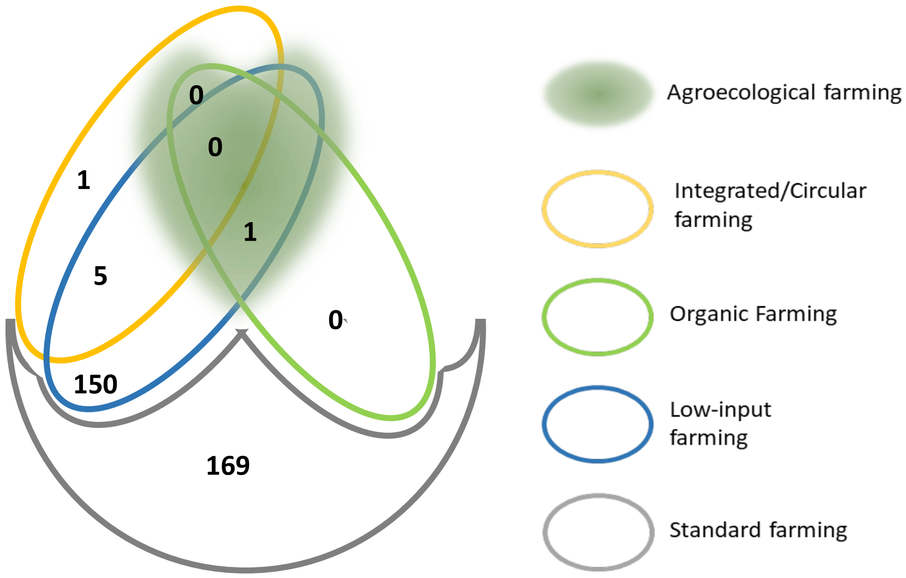

Figure A2. Typology of Irish dairy farms, 2014

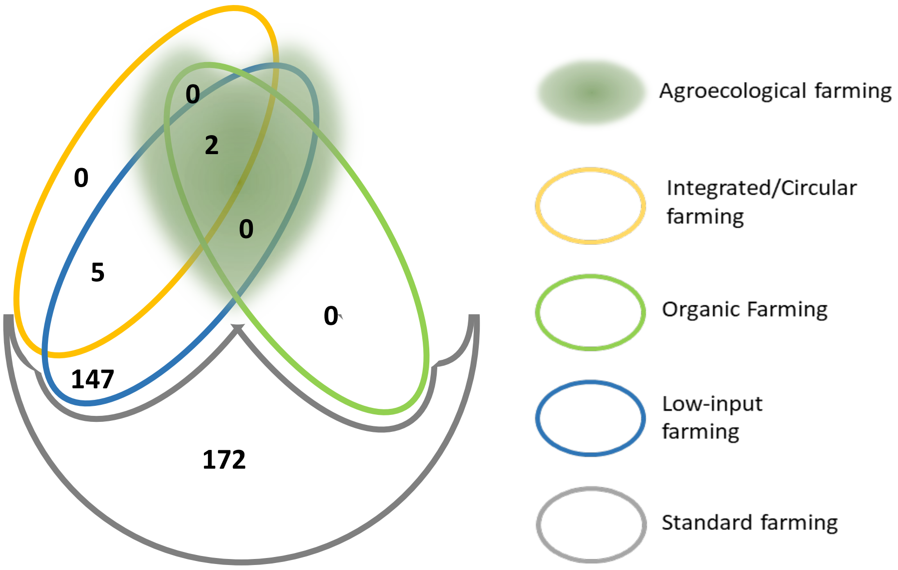

Figure A3. Typology of Irish dairy farms, 2015

Table A1: Economic indicators for dairy and beef farms, 2013 – 2015.

	Dairy farm			Beef farm		
Year	2013	2014	2015	2013	2014	2015
Private revenue-cost-ratio	1.28	1.47	1.43	0.88	0.93	1.05
Public revenue-cost-ratio	1.45	1.65	1.60	1.38	1.45	1.54
private revenue-cost-ratio (remuneration)*	0.97	1.07	1.03	0.57	0.56	0.62
Public revenue-cost-ratio (remuneration)*	1.09	1.19	1.15	0.86	0.83	0.88
Average product of land (Euros/ha)	3296	3343	3189	973	905	1014
Average product of labour (Euros/AWU)	121807	124365	121681	45899	42463	46653
Average product of capital	0.16	0.14	0.14	0.06	0.05	0.05
Average product of intermediary expenses	1.58	1.74	1.70	1.12	1.11	1.25
Equity ratio	0.95	0.96	0.95	0.98	0.99	0.99

*Calculated ratio considering remuneration of owned production factors

3.3 Modelling heterogeneous technologies in the presence of sample selection: The case of dairy farms and the adoption of agri-environmental schemes in France (INRAE)

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3.3.1 Introduction

We contribute to the literature that investigates the difference in economic performance between ecological farms and non-ecological farms. In the literature, two categories of ecological and non-ecological farms are identified based on recognised nomenclatures, such as participation or not in environmental schemes such as the Common Agricultural Policy (CAP) agri-environmental schemes (AESs). The present study suggests a methodology that allows to identify a further degree of ecological farming within the two categories through latent classes, which computes farms' technical efficiency while accounting for their production heterogeneity. We develop a model that enables correcting for the potential endogeneity associated with the adoption of AESs. The application is to French dairy farms in 2002-2016, using data from the French Farm Accountancy Data Network (FADN). In other words, we investigate for this sample whether there is a performance (technical efficiency) gap between more and less intensive farms, on the one hand in the sub-sample of farms with AESs, and on the other hand in the sub-sample of farms without AESs. This work is partly based on the article Dakpo et al. (2021a).

3.3.2 Description of case study region

The case study is the whole France. Dairy farming in France is mainly located in Western France (Brittany, Pays-de-Loire) with intensive farming producing milk, and mountainous regions (Auvergne, Rhône-Alpes, Franche-Comté) with more extensive farming producing high value cheese.

AESs aim to increase farmers' adoption of environmentally-friendly practices and are designed by European Union's member states. Farmers voluntarily adopt AESs, generally for five years, and receive payments to compensate for additional costs and potential profit losses following the adoption of environmentally-friendly practices. In France, in the case of grazing livestock farming, environmental practices covered by AESs relate to: the extent of permanent grassland; stocking rate; no-tillage and no pesticides on permanent grassland; set-up of ecological interest area; grass buffer strips; low use of nitrogen fertilisers; conversion to and maintenance of organic farming.

3.3.3 Method

We use the latent class stochastic frontier model (LCSFM), which simultaneously estimates the classes of farms depending on their technology, and each class's frontier (Orea and Kumbhakar, 2004; Greene, 2005). The distribution of farms into classes is based on the separating variables that capture more or less intensive technologies.

This approach had already been applied to dairy farms (and beef cattle farms and mixed dairy-beef farms) on French FADN data over 2002-2016 by Dakpo et al. (2021b). The authors used the following variables as separating variables: the livestock stocking rate; the share of permanent grassland in the utilised agricultural area (UAA); a capital intensity measured by the ratio of fixed assets per labour unit; environmental practices, proxied by the amount of AES subsidies per hectare of UAA; weather conditions, through average daily effective rainfall (in mm) and temperature (in degrees Celsius); a dummy for farm location in less favoured areas (LFA), and a time trend. The authors identified two classes with the LCSFM, one more intensive and one less intensive. The intensive class was on average more technically efficient than the extensive class for beef cattle and dairy farms. In contrast, in the case of mixed farms, the two classes had similar average technical efficiency.

In the current article, we extend the methodology of Dakpo et al. (2021b) to account for the fact that the adoption of AESs is endogenous. We extend Greene (2010)'s stochastic frontier sample selection model to account for production heterogeneity under the LCSFM. In this framework, endogeneity arises from the correlation between the two-sided error component in the production function and the sample selection equation noise. This sample selection equation is modelled as a probit with the following explanatory variables: milk price in Euros per ton of milk; farmer's age; farmer's low education dummy taking the value one if the farmer has a low level of education (that is, either no education or primary education) and zero if the farmer has a high level of education (secondary education or above); and 21 regional dummies. The sample selection parameter from this first step is integrated in the second step LCSFM.

The LCSFM is estimated separately for each sub-sample (sub-sample of farms with AESs; sub-sample of farms without AESs). In the LCSFM we specify the production function as a Translog output distance function with two outputs (the quantity of milk produced, and the other output value in constant Euros), five inputs (UAA in ha; total labour in full time equivalent annual working units; herd size in livestock units; intermediate consumption in constant Euros; and fixed assets excluding land and herd in constant Euros), year fixed effects and a dummy indicating whether the farm is located in LFA. Two separating variables are used in the LCSFM to identify the farm classes: the stocking rate, calculated as the number of livestock units per ha of UAA; and the share of permanent grassland in the UAA. The prior probability of farms belonging to a class change over specific periods (2002-2006, 2007-2013, and 2014-2016) and corresponds to the main CAP reforms, while it is fixed over time in the literature.

We simultaneously investigate the drivers of inefficiency, with the following variables: farmer's age; farmer's low education dummy; share of hired labour in total labour; share of rented area in UAA; CAP operational subsidies per ha (fully decoupled subsidies in the form of the Single Farm Payment, subsidies coupled to the acreage of specific crops and to the headage of specific livestock, subsidies received from adopting AESs, and subsidies received for being located in a LFA).

All computations are carried out using R software (R Core Team, 2020). The LCSFM is estimated with the R package sfaR (Dakpo et al., 2021c) which has been written in the framework of the LIFT project.

3.3.4 Data

We use the French FADN, managed by the French Ministry of Agriculture. We use the unbalanced database during 2002-2016, consisting of 15,436 observations in total. The farms in the full sample have on average a UAA of 90 ha and a herd of 99 livestock units. They use 1.9 annual working units of labour and produce 338 700 litres of milk for an average price of 340 Euros per ton. Their stocking rate is 1.2, and the share of permanent grassland in UAA is 40% on average. Farmers are 47 years old on average, and 24% of them have low education. The share of hired labour in total labour is 6%, and the share of rented area in UAA is 79% on average. They receive on average 378 Euros of operational subsidies per ha of UAA.

34% of the whole sample observations are in the sub-sample of farms with AESs. On average, output levels, milk yield, herd size, and intermediate consumption are higher, but UAA and milk price are lower in the sub-sample of farms that do not have AESs than the sub-sample of farms with AESs. About 75% of the farms with AESs are located in LFAs, while this proportion is 36% for the farms without AESs. Regarding separating variables, the stocking rate is higher, and the share of permanent grassland in UAA is lower for farms with no AESs than for farms with AESs.

3.3.5 Results

The first step selection model results show that the probability of having AESs increases with milk price, decreases with age, and increases with low education attainment. The result regarding education is not in line with the literature (Siebert et al., 2006).

For each sub-sample, the LCSFM results show differences in coefficients and elasticities between the model estimated on the full sub-sample (single-class) and the two-class model, highlighting the importance of accounting for technological heterogeneity in the frontier estimation. In addition, results show that the selectivity parameter is significant, confirming the presence of sample selection bias and the necessity to correct for the bias with the first-step probit model.

For each of the two sub-samples (farms with AESs and farms without AESs) results identified one class with extensive technology and one class with intensive technology: the probability of belonging to one of the two classes (which is then called the extensive class) is indeed positively associated with a higher share of permanent grassland in UAA, and negatively (for the sub-sample of farms with AESs) or non-significantly (for the sub-sample of farms without AESs) associated with a higher stocking rate. For both sub-samples, the farms in the intensive class rely less on permanent grassland and more on external inputs such as pesticides, fertilisers and concentrated feed, than the farms in the extensive class. On average, the intensive class is paid a lower milk price than the extensive class for both sub-samples (AES adopters and AES non adopters), and receives more CAP operational subsidies per ha of UAA. Despite this, the ratio of revenue to revenue plus subsidies (indicating the degree of market orientation for the farms), shown in Table 1, is significantly higher for the intensive class than the extensive class. As regard performance, in each sub-sample, the intensive class is significantly better performing than the extensive class in terms of all performance indicators presented in Table 1: technical efficiency, partial productivity ratios, cost-revenue indicators.

As regards the inefficiency drivers for the sub-sample of farms with AESs, in both classes the level of operational subsidies per hectare of UAA negatively influences technical efficiency. While farmer's age increases efficiency in the extensive class, the effect is reversed in the intensive class. The low education variable negatively affects the extensive class's efficiency and is non-significant in the intensive class. For this latter class, the share of rented area increases the efficiency level while in the extensive class, it is the share of hired labour that improves efficiency; the other effects are non-significant. As regards the inefficiency drivers for the sub-sample of farms without AESs, low education decreases efficiency for both classes. Operational subsidies per ha of UAA decrease efficiency for the extensive class only, and increase it for the intensive class. The impact of the share of rented area is positive on efficiency for the intensive class and non-significant for the extensive class. The share of hired labour has no significant effect in either class.

Table 1: Comparison of technical-economic performance of the extensive and intensives classes in both sub-samples

	Sub-sample of AES adopters			Sub-sample of AES non-adopters		
Variables	Extensive class	Intensive class	t-test of equality of means (p-value)	Extensive class	Intensive class	t-test of equality of means (p-value)
Milk volume per milking cow (tons per cow)	5.31	6.16	<1e-3	5.75	6.95	<1e-3
Total output to UAA (Euros/ha)	1,678	2,260	<1e-3	2,190	2,771	<1e-3
Total output to labour (Euros/AWU)	93,441	105,058	<1e-3	106,422	121,893	<1e-3
Total output to capital	0.76	0.88	<1e-3	0.88	1.09	<1e-3
Total output to intermediate consumption	2.205	2.208	0.09	1.93	2.01	<1e-3
Technical efficiency	0.85	0.98	<1e-3	0.84	0.95	<1e-3
Private revenue-cost-ratio not considering remuneration of owned production factors [a]	1.06	1.13	<1e-3	1.03	1.15	<1e-3
Public revenue-cost-ratio not considering remuneration of owned production factors [b]	1.36	1.38	<1e-3	1.25	1.34	<1e-3
Private revenue-cost-ratio considering remuneration of owned production factors [c]	0.69	0.75	<1e-3	0.72	0.80	<1e-3
Public revenue-cost-ratio considering remuneration of owned production factors [d]	0.88	0.92	<1e-3	0.87	0.94	<1e-3
Revenue to revenue and subsidies	0.78	0.81	<1e-3	0.83	0.86	<1e-3
Equity to total assets	0.53	0.58	<1e-3	0.64	0.68	<1e-3
Number of observations	2,759	2,515	<1e-3	4,495	5,667	<1e-3

[a] : Revenue / (intermediate consumption + depreciation + paid interest + paid labour + paid rent). It shows the ability of a farm to cover costs with its private revenues, except for costs for owned production factors.

[b] : (Revenue + subsidies) / (intermediate consumption + depreciation + paid interest + paid labour + paid rent). It shows the ability of a farm to cover costs with its private and public revenues, except for costs for owned production.

[c] : Revenue / (intermediate consumption + depreciation + paid interest + paid labour + paid rent + imputed labour + imputed rent). It shows the ability of a farm to cover costs with its private revenues, including those for costs for owned production factors (except for imputed interest which were not possible to compute).

[d] : (Revenue + subsidies) / (intermediate consumption + depreciation + paid interest + paid labour + paid rent + imputed labour + imputed rent). It shows the ability of a farm to cover costs with its private and public revenues, including those for costs for owned production factors (except for imputed interest which were not possible to compute).

3.3.6 Conclusion

The approach used in this article, namely a LCSFM with a first-step sample selection equation, allows identifying a range of ecological farms. Our findings indeed show that heterogeneity can be reflected in terms of more or less intensive technology within farms that have adopted AESs and within farms that have not adopted AESs. In total, four classes are identified from the most extensive (the extensive class in the AESs adopters sub-sample) to the most intensive (the intensive class in the AESs non-adopters sub-sample). From a policy point of view, it suggests that there is additional room to give incentives to farmers to modify their technology, even for farmers who are already engaged in an AES.

The main divergence in findings between the LCSFM for the sub-sample of farms with AESs and the LCSFM for the sub-sample of farms without AESs, relates to the impact of operational subsidies per ha on efficiency. Our results, therefore, underline that, from a policy point of view, accounting for heterogeneity both in terms of intensive and extensive technology and in terms of the adoption of AESs, could help better target the CAP.

Future research with this approach needs to account for intra-class heterogeneity (fixed or random effects) with panel data.

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3.4 The economic performance of transitional and non-transitional organic dairy farms: A panel data econometric approach in Brittany (INRAE)

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3.4.1 Introduction

The existing literature on the drivers of farm performance in organic farms, compared to conventional farms, is extensive, but it is still difficult today to identify the specific performance outcomes of organic farms insofar as the samples are very small (Dedieu et al. 2017). The results obtained also highly depend on the regions and the agricultural sector studied, the economic performance indicators, and the method used to avoid bias in the comparison between production systems. There is no consensus in the scientific literature. In this study, we propose to compare the economic and financial performance of both conventional and organic dairy farms, and our analysis differs from the existing literature in two ways. First, we use a fixed-effects and random-effects model to exploit the longitudinal dimension of our data and attempt to identify the specific effect of belonging to an organic label on the economic performance of farms. This first step allows us to explore the potential effects of other potential determinants, such as size, more or less intensive production system, and other unobservable individual characteristics. Second, we complete this study by analysing the impact of the conversion period on the performance of organic farms.

3.4.2 Description of case study region

The analysis is carried out on dairy farms in the department of Ille-et-Vilaine (NUTS3 level) in the region Brittany in the northwest of France. This is the leading French department in terms of milk production. Organic milk represents more than 10% of the volume of milk collected in this department. The studied territory is relatively homogeneous in terms of pedo-climatic conditions. We classify the farms into 3 categories: organic farming systems (after conversion), conventional-corn systems and grassland systems. To distinguish "corn" systems from "grassland" systems, we use the criteria set in the framework of the "mixed farming system" agro-environmental climate measures (MAEC - SPE) implemented with the 2015 CAP. To receive a payment, the contracting farms must respect, among other things, constraints on their share of corn and grass in their farm. In this study, we consider a system to be grassland when its share of corn in the main forage area (MFA) is less than 28% and its share of grass in the utilised agricultural area (UAA) is greater than 55%, which corresponds to the necessary conditions of this MAEC to obtain the lowest remuneration (MAEC type "SPE3"). As the farms in this last category are very numerous and heterogeneous, we propose to distinguish two subgroups of corn systems according to their share of corn fodder in the main forage area (MFA) based on a statistical classification that distinguishes the most intensive systems (corn system 1) from the others (corn system 2).

3.4.3 Method

We propose to compare the economic and financial performance of both conventional and organic dairy farms. First, we use a fixed-effects and random-effects model to exploit the longitudinal dimension of our data and attempt to identify the specific effect of belonging to an organic label on the economic performance of farms. Second, we complete this study by analysing the impact of the conversion period on the performance of organic farms.

3.4.3.1 Economic and financial performance indicators

To measure the performance of farms and their ability to cope with production or market shocks, we rely on traditional performance indicators. These are based on four dimensions of the economic and financial performance of the farm: its profitability, return on assets, solvency and liquidity (Wolf et al. 2016; Picaud, Ridier and Ropars-Collet, 2015).

We approach the profitability of farms, i.e., their capacity to create wealth, by controlling their intermediate consumption via two main indicators: on the one hand, the ratio of net profit to sales known as the gross profit margin (GPM) or margin rate, shows the percentage of sales that a company retains after covering all costs; on the other hand, EBITDA or gross operating profit, is the second indicator of profitability that measures the wealth created by the company once intermediate consumption and salary costs have been removed from production and operating subsidies (mainly CAP subsidies) have been added. In the analysis of profitability, we also use the milk gross margin (GM) indicator per litre of milk produced. This indicator balances milk sales and operating expenses (costs of feed purchases, veterinary and breeding expenses) of dairy activity. The rate of return on assets (ROA) is defined as operating income divided by total assets and reflects the ability of firms to use assets, both fixed and current, to generate profits. The debt-to-asset ratio (DA) is used to assess the solvency of firms. It is the ratio of total debt to total assets of the firm. The current ratio (CR) is a liquidity ratio that indicates the amount of cash and cash equivalents in proportion to short-term obligations, measuring the capacity of a firm to meet its short-term obligations. To complete our approach to the solvency of the firm, we use a final indicator, cash flow. Cash flow (CF) is equal to the balance between, on the one hand, the resources that the firm generates in the long term as a result of its policy of financing fixed assets and the income from its activity and, on the other hand, the financing needs of the activity in the short term (working capital requirements). The elements likely to influence cash flow are both "top line" elements (investments, such as those made during the conversion, and the results of previous years) and "bottom line" elements (inventories, operating debts and receivables). A positive cash flow reflects the flexibility of firms to deal with unforeseen events without having to rely on external funds. A negative cash flow indicates short-term borrowing and a shortage of cash. This indicator, therefore, provides insights into the financial health of a farm. The interpretation of this indicator remains delicate, however, since the level of cash flow is essentially very volatile, as it is highly dependent on market or weather volatility in a given year as well as on investment choices, which vary greatly from one company to another. These indicators reflect the short-term performance of farms. One indicator that can measure the long-term performance of firms is the total growth rate of assets (GRA). It measures the percentage change in a firm's assets from one year to the next and is equal to the total assets of one year over the total assets of the previous year minus 1. This indicator reflects the increase in the size and financial strength of a firm from one year to the next.

3.4.3.2 The linear mixed-effects model

The economic and financial performance of farms can be influenced by multiple factors: improved productivity allowed by better technical performance (linked to the characteristics of the farm such as its size and its level of mechanisation, or to the characteristics of the farmer such as his individual skills, experience and training), exogenous factors such as climate or a more favourable price situation, or the existence of better prices durably linked to belonging to a label such as organic. To differentiate the impact of individual farm specificities on their performance from the effects induced by organic farming, we build a linear mixed-effects model, as done by Wolf et al. (2016) on U.S. dairy farms. The interest in this statistical model is to control, in a simple way, for individual specifics via a random effect and time specifics via a fixed effect to identify the impact of organic farming on performance via another fixed effect.

Indeed, the random effect allows us to take into account only the variability related to the farm, without having to detail in the model those variables describing the specificities of the farms in terms of agricultural practices or farm structure. This variability is taken into account by adding to the model a random constant u_i specific to each farm. This random effect is characterised by a variance parameter that must be estimated in addition to the variance of the model errors ε_{itk}. The random variable u_i follows a normal distribution $N(0, \sigma_u^2)$, where σ_u^2 is the inter-subject variance. The random variable ε_{itk} follows a normal distribution $N(0, \sigma_\varepsilon^2)$, where σ_ε^2 is the within-subject variance. We assume that these random variables u_i and ε_{itk} are independent.

The fixed effects allow us to control for a possible time effect and to identify whether belonging to a group, particularly to the group of organic farms, impacts the economic and financial performance of the farms, following this equation:

$$y_{itk} = \mu + \gamma_t + \tau_k + (\gamma\tau)_{tk} + u_i + \varepsilon_{itk}$$

y_{itk} corresponds to the performance indicator observed at time t of individual i in group k; and the fixed effect term μ corresponds to the mean. The term γ_t represents the deviation from the mean associated with time t. The term τ_k represents the deviation from the mean associated with group k. In our model, we will define two groups, one group representing the production systems, in particular the organic farming system, and the other group representing the size of the farms. The term$(\gamma\tau)_{tk}$ represents the deviation from the mean associated with the interaction of time and group k. The term u_i is an individual random effect, and the term ε_{itk} corresponds to the residual. The term $\mu + \gamma_t + \tau_k + (\gamma\tau)_{tk}$ corresponds to the fixed and deterministic part of the model, while the term $u_i + \varepsilon_{itkh}$ corresponds to the random part.

3.4.4 Data

We have individual accounting data provided by CER FRANCE Brocéliande (a management and accountancy agency for farms operating in the department of Ille-et-Vilaine, Brittany). This database lists the private accounting data of both organic and conventional dairy farms in Ille-et-Vilaine. It contains 1,016 dairy farms, 95 of which are or are converting to organic farming during the period. We have an unbalanced panel over 10 years; from 2007 to 2017, each farm was followed between 2 and 10 years, for a total of 5,918 observations.

The comparison of the performances according to the production system (organic and non-organic) is carried out on this complete sample. The analysis of the impact of the conversion to organic on the performances is carried out on a sample composed of farms that are in an organic system or that converted to organic farming during our study period. We have 313 observations over 3 periods, 144 observations before conversion, and 53 observations during conversion, which we define as the year of conversion plus 3 years, and 116 observations after conversion.

3.4.5 Results

3.4.5.1 Descriptive statistics of the data

We identified a few characteristics of organic systems (especially in the dairy sector) that we believe describe their production technology and on which there is a consensus in the literature. These findings are confirmed by the descriptive analysis of the different production systems in terms of structural, agronomic and economic characteristics (see Table 1). First, organic farmers value their agricultural products under the organic label and thus benefit from an increase in the value of their selling prices. On average, in our sample, the price of milk is between 20 and 25% higher in organic systems, which corresponds to a milk premium of between 50 and 100€/ton of milk, which can vary depending on the dairy collector. Second, organic farming is based on a sparing and efficient use of variable inputs, especially concentrates, fertilisers and agrochemicals. On average, in our sample, we observe operating expenses in relation to gross product that are approximately 15% lower for organic systems, thanks, in particular, to lower expenses for concentrates (219€/LV for organic systems compared to 362€/LV for the most represented corn-based systems). Third, given the lower use of concentrates, cattle feeding in organic systems is based essentially on grazed grass or grass silage, which requires more grassland. In our sample, the average UAA of organic farms is 80 ha (between 60 and 70 ha for other production systems), and 70% of this area is allocated to grassland (between 32 and 46% for corn systems). These last two points allow organic farmers to reach a higher level of food autonomy, which is generally considered a prerequisite for their conversion to organic production. Finally, organic dairy farms rely on animal/plant complementarity to manage soil fertility without the use of synthetic fertilisers and make greater use of meadows and grass to feed the herd to limit the use of external feed. They diversify their crop rotation by implementing longer rotations to manage disease and parasite problems without having to rely on agrochemicals. These complementarities are a source of economies of scope. The dairy farming systems in our sample are relatively homogeneous in the sense that they all produce cereals, forages and grassland, yet all of them do not necessarily make optimal use of the interactions between crop and animal production. Some farms seem to be moving towards a simplification pathway and a specialisation of dairy activity in search of economies of scale.

Thereafter, we describe the average economic and financial situation of each group based on the economic and financial performance indicators defined in the previous section (see Table 2). Finally, we analyse the distribution of farms in each production system according to their size, defined by the number of dairy cows (see Table 3). Overall, despite very similar technical and agronomic characteristics of the grassland and organic systems, the organic farms have gross margins per litre of milk produced that are higher on average than the grassland group. On the other hand, the gross margin profit (GMP) and return on assets (ROA) indicators are quite close between the two production systems and seem to be higher than in the systems based on corn. In contrast, the solvency ratio appears to be lower on average for organic farms than for conventional farms. This can be explained by a higher level of investment during the conversion phase (e.g., the purchase of animals and equipment, which is confirmed by the greater proportion of large herds in the organic group), which can lead to an increased level of debt. In terms of herd size, the difference was also significant between grassland and organic systems. More than 80% of the grassland systems are small or medium sized, whereas the organic systems are mostly (54%) in the large class (more than 60 cows), which can also be explained by a lower average level of milk productivity than in the grassland systems (i.e., to achieve the same volume, more cows are needed). In addition, if we consider the level of productivity per cow by size class and by system, it appears that, in the grassland sector, the increase in herd size is not accompanied by a significant change in the level of milk productivity, whereas in the organic sector, this change from small to large herds results in a decrease of 1,000 litres per cow (cf. Table 4). Thus, in organic systems, a larger herd size seems to be accompanied by lower milk productivity, as the decrease in milk productivity with size may be a source of diseconomies of scale.

The conversion to organic farming in dairy systems is also accompanied by an increase in assets (capitalisation - GRA indicator in Table 2). This increase seems, on average, to be accompanied by an increase in the rate of return on capital, which would indicate the presence of economies of scale (the investments would be profitable because of higher market prices than conventional milk and lower feed costs).

Table 1: Statistical description of farm categories.

	Corn system 1	**Corn system 2**	**Grass system**	**Organic system**
Number of observations	1 493	3 773	483	169
UAA	69 ha	67 ha	61 ha	80 ha
Share of FC/MFA	53%	38%	21%	16%
Share of grass/MFA	32%	46%	67%	70%
Share of crops/UAA	36%	25%	16%	20%
Total milk produced	434 000 litres	372 000 litres	396 000 litres	376 000 litres
Milk produced per cow	7 657 litres/cow	7 144 litres/cow	6 418 litres/cow	6 075 litres/cow
Number of dairy cows	55.89	52.39	49.34	67.84
Animal density	1.26 cow/ha MFA	1.09 cow/ha MFA	0.96 cow/ha MFA	1. 00 cow/ha MFA
Price of milk	€331/1000 l	€331/1000 l	€337/1000 l	€412/1000 l
Total aid	€792/ha	€736/ha	€715/ha	€933/ha
Concentrated costs	€443/cow	€362/cow	€266/cow	€219/cow
Operating expenses/GP	40%	38%	34%	29%
Operating costs/litre	0.18	0.18	0.17	0.18
Share of feed produced	36%	32%	42%	62%
Asset value	€ 395 000	€ 339 000	€ 304 000	€ 494 000€
Operating expenses/GP	40%	38%	34%	29%

Notes: FC: fodder corn; MFA: main forage area; UAA: useful agricultural area; GP: gross product

Table 2: Financial performance of farms.

	Corn system 1	Corn system 2	Grass system	Organic system
GM	222 €/1000 l	235 €/1000 l	260 €/1000 l	338 €/1000 l
EBITDA	54.99 M€	48.04 M€	45.90 M€	80.35 M€
Ratio M	7.91%	8.80%	11.81%	11.71%
Ratio ROA	5.27%	5.75%	6.86%	7.43%
Ratio DA	39.49%	35.93%	32.52%	45.09%
Ratio NC	-2 398	2 790	11 705	4 500
Ratio GRA	0.057	0.049	0.029	0.126

GM: gross margin per litre of milk; EBITDA: gross operating profit; GPM: margin rate; ROA: return on assets, DA: debt on assets; CF: net cash flow; GRA: annual growth rate of assets.

Table 3: Distribution of farms by herd size.

Number of dairy cows	<40 dairy cows	[40 – 60] dairy cows	> 60 dairy cows
Corn system 1	19%	48.5%	32.5%
Corn system 2	22%	53%	25%
Grass system	35%	47%	18%
Organic system	10%	35%	54%

Table 4: Milk productivity per cow of farms according to their system and herd size.

Number of dairy cows	<40 dairy cows	[40 – 60] dairy cows	> 60 dairy cows
Corn system 1	7 681 litres/cow	7 554 litres/cow	7 798 litres/cow
Corn system 2	7 096 litres/cow	7 134 litres/cow	7 206 litres/cow
Grass system	6 630 litres/cow	6 366 litres/cow	6 143 litres/cow
Organic system	6 914 litres/cow	6 088 litres/cow	5 912 litres/cow

3.4.5.2 Effect of production system to economic performance

The parameters associated with the fixed effects of the model are presented in Table 5. As expected, farm size, measured by the number of cows, significantly impacts almost all economic performance indicators, regardless of the production system. Profitability and return on assets indicators decrease with the size of the herd. On average, medium-sized farms experience a decrease in their margin and ROA compared to large farms by approximately 10%. The decline in profitability indicators reaches 17% for small farms. It can be assumed that this drop in performance is related to the lower milk yield per cow in these smaller herd sizes and/or the lower dilution of breeding costs that are included in the margin calculation. The descriptive statistics do not confirm this hypothesis, since the operating expenses per litre of milk are not significantly different according to the size of the farms (an average of between 0.17 and 0.18€/litre of milk for each size group) and the milk productivity is not lower for the smallest farms (cf. table 4). This effect of size would therefore be explained by economies of scale in the set of fixed costs. Several studies have previously described size as a driver of farm performance in dairy farms. Tauer and Mishra (2006) show that in American dairy farms, neither the variable cost of producing a unit of milk nor efficiency decreases significantly with farm size. Instead, the fixed cost of production per litre of milk decreases with farm size, and the farm becomes more profitable. However, Chavas (2001) argues that there is no evidence that these economies of scale persist beyond certain sizes.

Regarding profitability indicators, the results of our statistical approach confirm the descriptive statistics presented previously. The organic farms have on average a gross margin per litre of milk that is approximately 30% higher and a gross operating surplus that is approximately 40% higher than the other production systems in our sample. These results can be explained by their lower level of intermediate consumption associated with a significantly higher selling price of milk. On the other hand, the positive effect of the organic system on the profitability indicators seems to be partly neutralised in the small farms. Thus, organic farms with fewer than 40 cows have lower profitability in terms of milk margin and EBITDA than other production systems. The lower margin per litre of milk can be explained by higher structural costs when compared to the total volume of milk produced. These higher structural costs, which can also penalize EBITDA, may be the result of higher wage costs or purchases of services (insurance, etc.) that are not compensated by the higher price of milk.

As far as the indicator of return on assets (ROA) is concerned, and although organic systems were on average better performing than all other production systems (see Table 1), we do not find these results from our econometric model on the solvency (DA) and profitability (ROA) criteria. In contrast, our results show a significant decrease in the ROA of organic farms. This informs us on two points.

First, the lower ROA performance of organic systems can be explained by their investment strategy. Depending on the level of investment at the time of conversion, the level of structural expenses and assets in the denominator of the ratio, is more or less increased. This will mechanically translate into a decrease in the ROA ratio if the operating income, in the numerator, has not increased by the same proportion. It should be noted that many of the organic farms in our sample have been organic for less than 5 years. It is reasonable to estimate that it takes several years for an organic farm to generate profits proportionally higher than the capital invested at the time of conversion. It will be interesting to compare this result with the analysis of the performance of organic farms before, during and after conversion, which will be presented in the next section.

These mixed results on the medium-term profitability of organic farms are consistent with those of Khanal and Mishra (2018), who show that the impact of organic production is variable depending on the production orientation and the level of sales. Uematsu and Mishra (2012) also showed that, although they benefit from higher prices, organic farms also incur higher costs related to labour, marketing, and insurance, which are similar to structural expenses. We particularly find these effects in smaller organic farms.

On the other hand, the difference between the average value of the ROA and the result of our estimation shows that there is a strong diversity of organic farm models associated with different strategies and production conditions from one farm to another. Indeed, for some farms, the conversion to organic farming was accompanied by a strong increase in capital. Others, on the contrary, have maintained a low capital intensity. The heterogeneity of these farms may also stem from their very different adaptation strategies in the face of climatic shocks. Indeed, these systems are probably more sensitive to climatic hazards, as animal feeding is less based on the use of concentrates and purchased feeds that would compensate for variations in forage yields, as is the case in corn systems. Thus, faced with unfavourable weather conditions, these farms will have to make decisions to ensure the feeding of their herd, which will depend, among other things, on the characteristics of their farm (e.g., location and quality of their soil and plot of land, etc.) and their managerial capacity. The different strategies adopted by the farmers are probably another source of heterogeneity within the organic group. It is also possible that this greater heterogeneity is artificial in the sense that the number of organic farms observed is not sufficient to highlight effects based on average values.

The comparative analysis of economic and financial performance between the different production systems allows us to highlight different determinants between non-organic and organic grazing systems, whereas one might have suspected similar results (Dieulot, 2015). Thus, although these two systems share common characteristics, in particular the search for food autonomy and spare management of inputs (lower level of variable expenses), we observe a significant difference in the rate of increase of assets. Organic systems have much higher levels of investment, linked to greater quantities of dairy cows (compensating for the lower productivity per cow) for the same volume of milk, and more fodder stocks, whereas fixed expenses remain low in grassland systems.

Table 5: Estimation of fixed effects

	GM	EBITDA	GPM	ROA	DA	CF	GCA
Constant	207.05**	62.62**	12.59**	9.19**	32.98**	28.18**	-0.01
Herd-size effect (small)	-2.58**	-36.30**	-8.60**	-5.96**	-7.84**	-25.90*	0.06
Herd-size effect (medium)	2.11	-20.07**	-1.98	-0.67	-6.32**	-17.50**	-0.03
System effect (organic)	70.09**	26.79**	-3.19	-5.18**	3.10	18.65	0.20**
System effect (grassland)	-4.04	-5.55	-1.85	-2.96	2.87	26.63**	-0.04
System effect (fodder corn 2)	-2.82	3.77	3.19*	0.81	3.08	9.49	0.03
Interaction effect (organic*small)	-26.80**	-16.71**	-2.36	-1.68	7.73*	-6.34	0.05
Interaction effect (organic * medium)	-11.27	-20.49**	-2.10	-0.47	-4.88	6.04	-0.002
Interaction effect (grassland * small)	-4.35	1.77	1.13	1.29	-0.36	-11.87	0.01
Interaction effect (grassland * medium)	-6.99	-1.44	-0.42	0.34	0.13	-11.63	0.04
Interaction effect (corn 2* small)	5.86*	2.78	1.58	1.36	-0.46	-4.82	-0.009
Interaction effect (corn 2*medium)	2.04	0.92	0.54	0.96	-0.41	-3.25	-0.02
R2	0.80	0.75	0.60	0.59	0.77	0.70	0.32

** and * statistically *different* from zero *at* the respectively 5% and 10% level *of* confidence. GM: gross margin per litre of milk; EBITDA: gross operating profit; GPM: margin rate; ROA: return on assets, DA: debt on assets; CF: net cash flow; GCA: annual growth rate of assets.

3.4.5.3 Effect of conversion to an organic system

Using the same approach as above, we seek to identify the effect of conversion, if any, on economic and financial performance. An effect related to the period before, during and after conversion is thus integrated into the model. We do not have enough observations in each size group to take into account a size effect. The constant corresponds to the farms before conversion. The parameters associated with the fixed effects of this model are presented in Table 6.

Table 6: Fixed effects estimates

	GM	EBITDA	GPM	ROA	DA	CF	GCA
Constant	337.06**	125.70**	31.17**	20.43**	45.29**	178.35**	-1.65**
Conversion effect (during)	-33.54*	-76.16**	-18.19**	-13.04**	7.12	-83.71**	1.58**
Conversion effect (after)	13.86	-24.75	-16.15	-10.94**	14.77	-19.70**	1.00**
R2	0.91	0.76	0.62	0.93	0.73	0.73	0.70

** and * statistically *different* from zero *at* the respectively 5% and 10% level *of* confidence. GM: gross margin per litre of milk; EBITDA: gross operating profit; GPM: margin rate; ROA: return on assets, DA: debt on assets; CF: net cash flow; GCA: annual growth rate of assets.

All profitability and cash flow indicators deteriorate during the conversion period, which is consistent with the increase in assets and the fact that the farms do not yet benefit from the capital gain on sale prices. After the conversion period, we observe, on the one hand, that even though all indicators have improved, the ROA and net cash flow rates are still significantly lower than their pre-conversion levels and, on the other hand, that the profitability indicators (GM, EBITDA and GPM) are not significantly higher than their pre-conversion levels. We also note that the constant of all profitability indicators, which represents the average before the conversion period, is much higher than the constant obtained in the first full sample estimation model, which represents the average of the indicators for large farms in corn systems (Table 5).

There are several possible explanations for these results. This may mean that the farms that convert to organic production have a higher profitability performance before conversion than the other systems in our sample. The positive impact of the organic group in the profitability models of the full sample (Table 6) would therefore not be directly related to the organic label alone but also to the specific characteristics of these farms. At the same time, it can be assumed that farms are gradually converting to organic farming, combining both conventional and organic farming. The transition to new practices and associated investments may therefore have started before the official conversion period (Argilés and Brown 2007).

The high heterogeneity of farms in organic systems, or the low number of observations, may also explain the lack of significance of the post-conversion period on the indicators. It would be necessary to follow the farms converted to organic farming over a greater number of years after conversion to identify significant effects. The strong and relatively recent development of organic farming, however, does not allow us to access such data series.

3.4.6 Discussion and conclusions

In this work, we confirm some known results on the determinants of heterogeneity of economic and financial performance of organic dairy cattle farms. While organic farms have higher average profitability and return indicators, we highlight other explanations for the differences in performance observed in the sample. Following Wolf et al.'s (2016) approach, we use a mixed-effects panel model, which controls, in a simple way, for individual specifics via a random effect and time specifics via a fixed effect, to identify the impact of organic farming on performance via another fixed effect.

As expected, farm size, measured by the number of cows, significantly impacts almost all economic performance indicators, regardless of the production system. However, if the organic farms have, on average, a higher gross margin per litre of milk and a higher gross operating profit compared to the other production systems in our sample, the effect of the size on the dilution of fixed costs and economies of scale takes a particular turn in the organic system. Indeed, it is difficult to increase the milk yield per cow by forgoing synthetic chemical inputs and by relying more heavily on a diet based on produced forages. Thus, we observe that the average annual growth rate of assets is higher for the organic farmers in our sample because of the increase in capital (herd) and stocks (forage) to produce the same volume of milk. In addition, despite lower variable costs per litre of milk (especially in feed purchases) and higher organic prices, additional fixed costs can occur in the organic system that are related to the workload or to the possible purchase of additional services. Consequently, only the largest herd sizes (over 40 cows) manage to maintain higher average profitability, while small organic herds are less profitable. However, these results must be qualified according to the conversion trajectories followed by the farms, which are undoubtedly very heterogeneous (some resulting in higher capitalisation, others in maintaining the capitalisation level).

Regarding the production system, while one could have expected comparable economic performances between organic and grassland farms, which are both seeking food and fodder autonomy, it appears that the increase in assets is the prerogative of organic farms. The latter have higher levels of investment, linked to a larger number of dairy cows (compensating for lower productivity per cow) for the same volume of milk, as well as more fodder stocks, while fixed costs remain low in grassland systems.

We then analyse the effects of the conversion period on the economic performance of the farms using data from several years of follow-up. Thus, the conversion period is accompanied by a decrease in profitability, but the farms in conversion seem to be more efficient at the beginning than the average of the farms in the sample. Furthermore, the growth of assets in the organic sector may, at least temporarily, reduce their profitability if their income does not grow as fast as their assets. A longer observation period would allow us to have a more complete view of the long-term profitability of organic farms.

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3.5 Investments, ecological approaches, environmental subsidies and the productivity of Italian farms (UNIBO)

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3.5.1 Introduction

The sustainability of the agricultural sector is a key challenge. In Italy, in response to both market (Willer et al., 2021) and policy incentives (Casolani et al., 2021), an increasing number of farms have converted to organic production (Willer et al., 2021). Moreover, anecdotical evidence shows that, next to organic, other numerous schemes incentivising the uptake of ecological approaches in agriculture are in place (Schaller et al., 2020). However, the reduction of the intensity of agriculture is rather controversial (Phalan et al., 2011), and relevant questions are to what extent different degree of ecological approaches are characterised in terms of productivity.

This research investigates the impact of private investment and environmental subsidies on Italian farms' performance, measured by total factor productivity (TFP) and two partial productivities, for the period 2010-2013. The analysis is performed, taking into account fixed farms characteristics, such as location, type of farming activities and the degree of ecological approaches.

3.5.2 Description of the case study region

Italy is a high-income country located in the South of Europe, with a population of 60.4 million inhabitants, being the majority (70%) urban. Italy has an extension of 302,073 km^2 and a coastline of 7,468 km (CARISMAND, 2016). Due to its rather longitudinal extension (1,180 km), Italy has a Mediterranean but diverse climate and geography. The climate in Northern regions is characterised by relatively long winters and extreme temperatures during winter and summer. The climate is milder, and summers are longer in Central Italy, with less temperature variation between seasons. The Southern regions and the islands have milder winters and hotter spring and autumns (Italian National Tourist Board, 2021). Italian topography is also diverse: 35% of its land is mountainous, 42% hilly, 23% plain. This geographical variety enables highly diversified agricultural systems and specialised agri-food products (CREA, 2020).

Italy's gross domestic product (GDP) in 2019 was 2.004 trillion Euro, and the GDP per capita stood at 33,225 Euro (The World Bank, 2021), with however major regional differences. Agricultural areas represent 42% of the Italian land area, but the agricultural sector only represents 1.9% of the GDP. There are major regional differences also in terms of agricultural specialisations. Southern regions produce fruits, vegetables, olive oil, wine, and durum wheat; while grains, soybeans, meat, and dairy products are mainly produced in the North of Italy. In 2016, the majority of the Italian farms were specialist in permanent crops and arable crops (47% and 30%, respectively), followed by specialist herbivorous and mixed-cultivation (9% and 8%, respectively), while the least representative farm productive orientation was mixed-breeding (0.32%) (CREA, 2020).

3.5.3 Method

The empirical analysis is divided into three steps: 1) farms' performance estimation, 2) farms' degree of ecological approaches classification, 3) exogenous and endogenous drivers of technical-economic farms' performance levels assessment.

In the first stage, to assess the technical-economic performance of the farm, we estimate two partial productivity indicators and the total factor productivity (TFP). The two partial productivity indicators we take into account are: i) the Average product of land and ii) the Average product of labour. The aforementioned indicators are estimated as depicted by Equation (1):

$$\boldsymbol{Partial\,productivity_t} = \frac{\boldsymbol{Output_t}}{\boldsymbol{Input_t}} \tag{1}$$

where, at time t, *Partial productivity* refers to the farms' Average product of land or Average product of labour, *Output*$_t$ represents the farms' total output (in Euro), and *Input*$_t$ stands for input land (in hectares) or input labour (in AWU[5]).

We estimate TFP using the Levinsohn and Petrin (2003) method that assumes the production function to be Cobb–Douglas, as described by Equation (2):

$$\boldsymbol{y_t = \alpha_0 + \alpha_k k_t + \alpha_l l_t + \alpha_m m_t + \omega_t + \eta_t} \tag{2}$$

where, at time t, y_t represents the firms' output, k_t is the state variable for input capital, l_t denotes the freely variable inputs (labour), m_t represents input material (or intermediate inputs), ω_t is the state variable first error term component that assumes firms' inputs choices to be influenced by the productivity derived from external factors (shocks), and η_t is the second error term which is assumed to be uncorrelated with firms' input choices. This approach uses materials (as energy, fertilisers, seeds, etc.) as proxies for unobservable productivity while accounting for the correlation between input levels and productivity (endogeneity), thus, avoiding inconsistent estimates or bias. The intermediate input m_t is assumed to be dependent on the state variables k_t and ω_t, hence: $m_t = m_t(k_t, \omega_t)$. After making assumptions on the firm's production technology, Levinsohn and Petrin (2003) show that the demand function is repeatedly increasing in ω_t, allowing for the inversion of the intermediate demand function and, hence: $\omega_t = \omega_t\,(k_t, m_t)$. After the parameters' estimation, the residuals of the estimation of the TFP can be written as per Equation (3):

$$\boldsymbol{TFP = \widehat{\eta_t + \xi_t} = v_t - \widehat{\beta_l} l_t - \beta_k^* k_t - \mathrm{E}\left[\omega_t \widehat{|\omega_{t-1}}\right]} \tag{3}$$

In the second stage, we classify the farms according to their degree of ecological approaches. We use two classification criteria. In the first classification, farms are categorised into 1) non-organic, 2) organic, and 3) transitioning into organic or "somehow organic". In the second classification, we use the protocol developed by Rega et al. (2019). Such a protocol categorises farming systems into *conventional* and three other non-mutually exclusive types, i.e., *integrated*, *low-input*, and *organic farming*. In order to apply the protocol, first, variables regarding the farms' characteristics[6] (i.e., altitude, geographical location) and productive inputs[7] (i.e., electricity, livestock feed) were identified and adjusted

[5] Annual working units (AWU), is a unit of measure that according to Eurostat (2019), refers to the full-time equivalent employment, in other words, 1 AWU corresponds to the work performed by one person who is occupied on an agricultural holding on a full-time basis, thus, no person can represent more than one AWU. In the case of Italy, we have used 1,800 hours as the minimum figure (225 working days of eight hours each).

[6] See description of farms' characteristic variables in Annex 1.

[7] See description of productive input variables in Annex2.

using deflation coefficients and the European price index[8]. Subsequently, farms were classified according to the bioregion where they belong to, using as indicators their geographical location and altitude. In Italy, farms can be considered Mediterranean, continental, and alpine[9]. Then, considering the type of farming classification (TF14 and TF8) and the farms' bioregion, each farm received a score depending on the use, purchase, and production of productive inputs. Finally, a score was calculated as the weighted average of all assigned scores, as shown in Equation (4):

$$Final\ score = \frac{\sum_{i=1}^{n} w_i * s_i}{\sum_{i=1}^{n} w_i} \tag{4}$$

where, s_i represents the score assigned to the i-th variable, and w_i is the corresponding weight. Farms that scored ≥ 3 were assigned to the assessed "Farming approach".

In the third stage of the analysis, we construct a correlational relationship that is designed to capture the effects of private investment and environmental subsidies, taking into consideration the farms' characteristics (independent variables), on TFP (dependent variable), as represented in Equation (5):

$$Performance_{ikt} = \beta_{okt} + \alpha_{jk} INV_{ijt} + \delta_{jk} ES_{ijt} + \gamma_{jk} OP_{ijt} + \theta_{jk} TF_{ijt} + \mu_{jk} R_{ijt} + \varepsilon_{ikt} \tag{5}$$

for i =1,…,n and k =1,…,m. In equation (5), $Performance_{ikt}$ is the k-th real value response for the i-th observation for *farms' partial productivity and TFP* at time t; INV_{ijt} is the j-th predictor for the i-th observation for *investment/hectares in Euro* at time t; ES_{ijt} is the j-th predictor for the i-th observation for *environmental subsidies/hectares in Euro* at time t; OP_{ijt} is the j-th predictor for the i-th observation for *organic practices* at time t (OP predictor for 8 organic practices[10]); TF_{ijt} is the j-th predictor for the i-th observation for *farming type classification* at time t (TF predictor for 14 farming type classification[11]); R_{ijt} is the j-th predictor for the i-th observation for *region* at time t (G predictor for 21 Italian regions[12] based on the Nomenclature of Units for Territorial Statistics (NUTS)-2 level); ε_{ikt} is a multivariate error predictor t.

3.5.4 Data

We use data extracted from the Farm Accountancy Data Network (FADN), which contains accounting information, such as income and business activities, of a representative sample of the EU farms. The sample is stratified according to region (NUTS2), economic size (SIZ6), and type of farming (TF14).

From the whole set of observations, we constructed a balanced dataset. For the first stage of the analysis, the estimation of the TFP, the balanced panel data included farms' information from 2004 to 2013. However, following the FADN-based protocol of "farming approach" implementation, the years 2004-

[8] More information in Comparative price levels of consumer goods and services: https://ec.europa.eu/eurostat/statistics-explained/index.php/Comparative_price_levels_of_consumer_goods_and_services#Price_levels_for_food.2C_beverages.2C_tobacco.2C_clothing_and_footwear.

[9] See description of farms' bioregion in Annex3.

[10] Conventional, Low input, Integrated, Organic, Low input + Integrated, Low input + organic, Organic + integrated, Low input + organic + integrated

[11] 15 Specialist COP, 16 Specialist other fieldcrops, 20 Specialist horticulture, 35 Specialist wine, 36 Specialist orchards – fruits, 37 Specialist olives, 38 Permanent crops combined, 45 Specialist milk, 48 Specialist sheep and goats, 49 Specialist cattle, 50 Specialist granivores, 60 Mixed crops, 70 Mixed livestock, 80 Mixed crops and livestock.

[12] 1 Piemonte, 2 Valle d'Aosta/Vallée d'Aoste, 3 Liguria , 4 Lombardia, 5 P.A. Bolzano/Bozen, 6 P.A. Trento, 7 Veneto, 8 Friuli-Venezia Giulia, 9 Emilia Romagna, 10 Toscana, 11 Umbria, 12 Marche, 13 Lazio, 14 Abruzzo, 15 Molise, 16 Campania, 17 Puglia, 18 Basilicata, 19 Calabria, 20 Sicilia, 21 Sardegna.

2009 were discarded. The panel data that we use for the second stage of our analysis include information of 2,117 Italian farms for the period 2010-2013 (8,468 observations) distributed among five macro-regions: Northwest (27.30%), Northeast (25.79%), Central (14.64%), South (25.27%), and Insular (6.99%) Italy. Most farms have an area smaller than 5 hectares (ha) and an economic size between 8,000 Euro and 25,000 Euro. The main farms' specialisations are field crops (31.41%) and other permanent crops (15.82%). During the considered period, 15.48% of the farms received environmental subsidies.

Table 2: Description of variables, Italy 2010-2013 (panel data)

	Variable	**Measurement**	**Measurement (in FADN)**	**Variable (in FADN)**	**Mean**	**Standard Deviation**	**Min**	**Max**
Variables								
	Land extension	Total Utilised Agricultural Area (in hectares –ha–)		se025	28.58	51.11	0.12	763.5
OUTPUT	Output	Value added	Farm net value added (in Euro)	se415	65,008.01	165,430.1	-460,084	2,962,124
OUTPUT	Output	Gross revenue	Total output (in Euro)	se131	116,119.50	285,172.4	0	7,105,055
INPUT	Labour input	Labour	Total labour input (in AWU)	se010	1.79	1.69	0.06	22.17
INPUT	Labour input	Cost of labour	Total wages paid (in Euro)	se370	8,313.99	26,656.73	0	322,400
INPUT	Material	Intermediate input	Total intermediate consumption (in Euro)	se275	51,707.68	152,384.7	215	5,431,983
INPUT	Capital input	Capital	Total assets (including land) (in Euro)	se436	761,296.60	1,589,821	5,475	26,866,323
INPUT	Capital input	Fixed Assets	Total fixed assets (in Euro)	se441	489,809.70	1,018,048	0	13,034,285
Variables standardised per hectares								
OUTPUT	Output	Value added	Farm net value added (Euro/ha)	va_ha	7,770.08	30,600.18	-35,944.10	1,188,498
OUTPUT	Output	Gross revenue	Total output (Euro/ha) (Average product of land)	prod_land	14,161.61	44,138.90	0	1,576,121
INPUT	Labour input	Labour	Total labour in put (AWU/ha)	lab_ha	0.36	0.77	0.003	13.58
INPUT	Labour input	Cost of labour	Total wages paid (in Euro)	lcost_hec	870.46	4,629.32	0	178,571.4
INPUT	Material	Intermediate input	Total intermediate consumption (Euro/ha)	mat_ha	4,939.52	14,819.59	27.20	458,391.4
INPUT	Capital input	Capital	Total assets (including land) (Euro/ha)	k_ha	69,717.23	124,356.5	498.29	2,587,711
INPUT	Capital input	Capital	Total assets (including land) (Euro/ha)	fix_ast_ha	41,950.31	70,552.7	0	1,920,305

Source: authors' calculation. (Notes: nr. of observations: 8,468).

For the production estimation, different models were tested using two outcome variables (total output and net farm's value added), and five input variables: total labour input and total wages paid (in Euro), total intermediate consumption (in Euro), total assets (in Euro), and fixed assets (in Euro). All these variables were standardised by hectares, using the variable *total utilised agricultural area* (in ha). The description of these variables is shown in Table 1. After testing the models, a final model for the production estimation was identified. This model uses as output indicator "Farm net value added (Euro/ha)", as capital input "Fixed assets (Euro/ha) – including land value", as labour input "Total labour input (AWU/ha)", and as material input "Total intermediate consumption (Euro/ha)".

3.5.5 Results

The results of the estimation of the Levinsohn-Petrin productivity estimation from Equation (2) and Equation (3) suggest that the input variables (labour, capital, and materials) are strong determinants of the farms' TFP, as shown in Table 2:

Table 3: Total factor productivity (TFP) estimation, Italy 2004-2013 (panel data)13

Variable	lnValue-added (Euro/ha)
lnLabour	0.395***
	(0.0130)
lnCapital	0.0316*
	(0.0187)
Observations	20,276
Groups	2,117
Group variable (i)	id
Time variable (t)	year
Observations per groups	Min = 10; Mean = 10; Max = 10
Wald test of constant returns to scale	Chi2 = 602.03 (p = 0.0000)
Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1	

Source: authors' calculation.

Table 3 describes the farms' performance variables obtained from Equation (1) and Equation (3), from the year 2010-2013, in total, and disaggregating them whether farms invested or not. Results show that, on average, farms that invest have higher levels of performance than farms that do not.

Table 4: Results of correlational relationship, Italy 2010-2013 (panel data)

Variable	Observations	Mean	Min	Max	Observations	Mean	Observations	Mean
		2010			Invested 2010		Did not invest 2010	
TFP	2,021	8,352.55	3.04	504,792.3	506	9,030.01	1,515	8,126.28
P.P. Land	2,117	14,140.54	57.93	1,493,242	535	15,219.75	1,582	13,775.58
P.P. Labour	2,117	51,877.52	1,810.35	1,055,274	535	61,735.73	1,582	48,543.68
		2011			Invested 2011		Did not invest 2011	
TFP	2,034	7,243.64	15.08	330,155.2	428	7,757.88	1,606	7,106.6
P.P. Land	2,117	14,648.96	51.81	1,576,121	453	13,085.64	1,664	15,074.55
P.P. Labour	2,117	50,731.2	2,725	768,522.8	453	61,880.36	1,664	47,696.01
		2012			Invested 2012		Did not invest 2012	

[13] Table 2. shows the results obtained from the TFP estimation on the first stage dataset that corresponds to the period 2004-2013. After implementing the FADN-based protocol of "farming approach", data was restricted to 2010-2013.

TFP	2,002	6,890.55	23.24	351,180.8	511	8,069.22	1,491	6,486.6
P.P. Land	2,117	14,155.68	123.82	1,453,637	543	19,688.45	1,574	12,246.98
P.P. Labour	2,117	51,538.04	2,930.88	736,028.3	543	59,009.9	1,574	48,960.39
		2013			**Invested 2013**		**Did not invest 2013**	
TFP	2,010	6,931.35	1.16	344,166.8	488	8,685.62	1,522	6,368.88
P.P. Land	2,117	13,701.25	0	1,435,020	523	19,566.91	1,594	11,776.69
P.P. Labour	2,117	50,332.22	0	654,088.4	523	53,750.66	1,594	49,210.61

Source: authors' calculation.

Table 4 illustrates the results of the FADN protocol and suggests that although most Italian farms (70%) use conventional production techniques, a significant percentage of Italian farms (30%) have adopted some ecological practices. Such practices, in general, look either at reducing soil disturbance, optimising the use and management of production inputs, and being sustainable. Moreover, results show that integrated farming systems represent 20% of the farms, suggesting that production practices are in-between organic and conventional among the farms studied.

Table 5: FADN protocol farming system, Italy 2010-2013 (panel data)

Farming system	Frequency
Conventional	5,931 (70.04)
Low input	72 (0.85)
Integrated	1,663 (19.64)
Organic	275 (3.25)
Low input + Integrated	323 (3.81)
Low input + organic	22 (0.26)
Organic + integrated	120 (1.42)
Low input + organic + integrated	62 (0.73)
Total	8,468 (100)

Source: authors' calculation. (Notes: percentage in parenthesis).

The results obtained from the application of Equation (5), shown in Table 5, suggest that, on average, farms' TFP, average product of land, and average product of labour are 0.87, 2.27, and 1.48 Euro higher for each Euro/ha invested. Moreover, farms that invest have on average more elevated levels of TFP, average product of land and average product of labour (8,407 Euro, 17,037 Euro, and 59,014 Euro, respectively) than those that do not invest (7,024 Euro, 13,240 Euro, and 48,592 Euro, respectively). These results hint at the fact that the farms' investments are efficiently utilised to improve production inputs and show that investing, on average, has a positive and significant effect on farms performance levels.

Concerning environmental subsidies, the results show that farms' TFP and average product of land increase of 1.57 and 10.17 Euro per Euro/ha received. Previous research on the effect of agri-environmental subsidies is inconclusive or ambiguous, showing different results depending on the composition of the sample, country characteristics, farms' size and time horizon (Arata & Sckokai, 2016; Baráth et al., 2020; Bernini et al., 2017; Latruffe et al., 2017; Latruffe & Desjeux, 2016; Mennig & Sauer, 2020; Nilsson, 2017). While other studies have found rather negative effects of subsidies on farms performance (Mary, 2013; Minviel & De Witte, 2017; Rizov et al., 2013). However, our results are consistent with those from the previous studies that show a positive relationship between subsidies and farms' productivity (Mennig & Sauer, 2020; Vigani & Curzi, 2019).

Regarding the degree of ecological approaches, results show that, on average, low-input, integrated, low-input+integrated, and organic+integrated farms have a significant negative relationship with TFP and partial productivities, while organic farms show a significant positive relationship with the average product of labour. Looking at the interactions between ecological approaches and investment results evidence that integrated and low-input+integrated farms that invest have a significant negative relationship with TFP and average product of land while organic+integrated farms have a significant negative relationship with average product of labour. However, low input farms that invest increase their level of TFP and average product of labour by 5.01 and 23.98 Euro for every Euro/ha they invest. Regarding the farms' characteristics, the analysis suggests that there are significant differences among regions, showing that in general, Lombardia, Liguria and P.A. Trento are the best performing regions. Results also show significant differences among specialisations regarding farms specialist cereals, oilseeds and protein crops (COP).

Table 6: Results of correlational relationship, Italy 2010-2013 (panel data)

Variables	TFP	Average product of land	Average product of labour
Total investment/hectare	0.87*** (0.16)	2.27*** (0.50)	1.48** (0.64)
Environmental subsidies/hectare	1.57*** (0.45)	10.17*** (1.46)	-1.95 (1.88)
Farms' ecological practices with respect to "1, conventional"			
2, Low input	-1,167.98 (1,482.75)	-8,119.10* (4,746.34)	-1,708.80 (6,127.08)
3, Integrated	-4,262.10*** (373.51)	-13,173.68*** (1,174.79)	-21,187.84*** (1,516.54)
4, Organic	-296.36 (782.67)	-4,023.48 (2,495.79)	9,172.00*** (3,221.84)
5, Low input + Integrated	-3,734.50*** (729.95)	-10,095.00*** (2,311.87)	-20,691.25*** (2,984.41)
6, Low input + organic	73.79 (2,610.85)	-3,300.23 (8,421.57)	12,117.34 (10,871.46)
7, Organic + integrated	-2,156.67* (1,140.55)	-7,260.74** (3,665.42)	-5,544.73 (4,731.72)
8, Low input + organic + integrated	-2,521.20 (1,595.66)	-8,464.65* (5,143.90)	-164.43 (6,640.30)
Interaction between farms' ecological practices and total investment/hectare with respect to "1, conventional # total investment/hectare"			
2, Low input # total investment/hectare	5.01** (1.97)	9.50 (6.34)	23.98*** (8.19)
3, Integrated # total investment/hectare	-1.09*** (0.29)	-3.91*** (0.91)	-0.55 (1.17)
4, Organic # total investment/hectare	-0.87 (0.81)	-1.05 (2.24)	-2.34 (2.89)
5, Low input + Integrated # total investment/hectare	-3.05** (1.42)	-12.68*** (4.59)	-3.42 (5.92)
6, Low input + organic # total investment/hectare	-2.53 (571.10)	116.67 (1,843.28)	1,879.39 (2,379.50)
7, Organic + integrated # total investment/hectare	-1.34 (1.34)	-0.86 (4.31)	-10.31* (5.57)
8, Low input + organic + integrated # total investment/hectare	0.41 (8.01)	-1.31 (25.86)	-20.12 (33.38)

Farms' geographical region with respect to "9, Emilia Romagna"			
1, Piemonte - (ITC1)	-179.71	-2,990.25	11,520.21***
	(911.81)	(2,855.53)	(3,686.22)
2, Valle d'Aosta/Vallée d'Aoste - (ITC2)	-2,545.60**	-2,370.55	-50,043.37***
	(1,121.82)	(3,557.78)	(4,592.76)
3, Liguria - (ITC3)	4,115.33***	15,624.43***	-16,350.16***
	(819.22)	(2,580.82)	(3,331.60)
4, Lombardy - (ITC4)	3,195.98***	2,419.40	26,458.52***
	(706.30)	(2,220.99)	(2,867.09)
5, P.A. Bolzano/Bozen - (ITH1(new)-ITD1(old))	1,736.79*	4,011.23	-25,347.71***
	(974.28)	(3,026.87)	(3,907.40)
6, P.A. Trento - (ITH2(new) -ITD2(old))	2,596.26***	8,619.18***	-6,740.33*
	(969.25)	(3,006.58)	(3,881.22)
7, Veneto - (ITH3(new) -ITD3(old))	898.34	209.45	10,300.44***
	(737.45)	(2,291.70)	(2,958.37)
8, Friuli-Venezia Giulia - (ITH4(new) -ITD4(old))	-1,137.33	-3,166.45	3,689.70
	(851.85)	(2,622.98)	(3,386.03)
10, Toscana - (ITI1(new) -ITE1(old))	-393.35	-1,186.76	-14,175.23***
	(937.57)	(2,914.32)	(3,762.11)
11, Umbria - (ITI2(new) -ITE2(old))	-499.83	-1,634.44	-10,409.85***
	(812.57)	(2,560.16)	(3,304.93)
12, Marche - (ITI3(new) -ITE3(old))	-2,398.65***	-3,482.91	-28,129.75***
	(884.72)	(2,757.86)	(3,560.14)
13, Lazio - (ITI4(new) -ITE4(old))	796.08	-491.11	-6,925.84
	(1,110.04)	(3,472.84)	(4,483.12)
14, Abruzzo - (ITF1)	-2,432.10***	-2,806.97	-28,020.54***
	(856.19)	(2,689.07)	(3,471.34)
15, Molise - (ITF2)	-1,772.66**	-2,499.74	-30,481.33***
	(814.34)	(2,558.08)	(3,302.25)
17, Puglia - (ITF4)	-1,583.82*	-2,034.59	-17,607.87***
	(885.36)	(2,780.23)	(3,589.02)
18, Basilicata - (ITF5)	-2,268.62***	-2,286.61	-26,702.75***
	(787.74)	(2,462.95)	(3,179.44)
19, Calabria - (ITF6)	536.17	-1,030.84	-26,729.38***
	(848.01)	(2,693.79)	(3,477.43)
20, Sicilia - (ITG1)	-1,897.17**	-2,524.93	-19,315.30***
	(804.61)	(2,530.34)	(3,266.44)
21, Sardinia - (ITG2)	-185.57	-610.29	-3,382.22
	(1,267.82)	(4,038.15)	(5,212.88)
Farms' specialisation with respect to "15, Specialist COP"			
16, Specialist other fieldcrops	3,898.11***	8,039.39***	5,825.28**
	(580.96)	(1,819.17)	(2,348.37)
20, Specialist horticulture	16,358.35***	59,903.48***	7,209.84**
	(702.53)	(2,207.23)	(2,849.34)
35, Specialist wine	4,985.20***	9,154.83***	-2,205.18
	(567.01)	(1,767.43)	(2,281.59)
36, Specialist orchards - fruits	6,152.05***	11,153.19***	-1,211.81
	(624.33)	(1,967.84)	(2,540.30)
37, Specialist olives	2,819.41***	4,812.06*	-4,759.60
	(841.56)	(2,661.16)	(3,435.31)
38, Permanent crops combined	3,224.81***	5,777.43**	-5,862.38*
	(822.54)	(2,604.20)	(3,361.78)
45, Specialist milk	4,291.86***	5,322.74***	40,363.01***
	(564.35)	(1,776.11)	(2,292.79)
48, Specialist sheep and goats	1,858.07**	3,914.97	-313.38
	(798.44)	(2,495.85)	(3,221.91)
49, Specialist cattle	2,395.18***	3,419.64	24,159.71***
	(713.41)	(2,213.37)	(2,857.25)
50, Specialist granivores	12,452.40***	24,386.26***	99,584.86***

	(892.15)	(2,805.45)	(3,621.57)
60, Mixed crops	2,195.53***	4,441.89**	-8,987.35***
	(625.80)	(1,961.40)	(2,531.98)
70, Mixed livestock	2,302.81	5,035.70	8,216.27
	(2,760.90)	(8,677.71)	(11,202.12)
80, Mixed crops and livestock	1,617.23**	3,797.27	-4,699.31
	(768.36)	(2,403.38)	(3,102.55)
Constant	2,817.14***	2,910.66	56,173.43***
	(684.06)	(2,131.20)	(2,751.18)
Observations	8,067	8,468	8,468
R-squared	0.22	0.26	0.29
Number of years	4	4	4

Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Source: authors' calculation.

3.5.6 Discussion and conclusions

This analysis provides insights into the relationship between private investment, agri-environmental subsidies, and farms' productivity, covering the period 2010-2013, using a balanced panel extracted from the FADN. Using fixed-effects panel analysis, we estimate the impact of investment, agri-environmental subsidies and different measures of ecological approaches on the farms' performances, proxied through the TFP and two partial productivity indicators. We contribute to the existing literature by looking at the effects of private investment and agri-environmental subsidies on farms' productivity, which are critical issues in applied policy analysis.

Results indicate that shifting from conventional to more ecologically-sound type of farming exhibits trade-offs in terms of reduction in productivity, both total and partial. These trade-offs can, however, be mitigated by investments. Indeed, our results show a consistently positive and significant relationship between agricultural investment and farms' performance, measured by TFP and average product of land and labour. Compared to previous studies, our research supports the positive relationship between environmental subsidies and farms' TFP and average product of land. On the one hand, these findings suggest the importance of fostering and enhancing private investment in farms to continue improving the holdings' productivity. On the other hand, they suggest the efficient allocation and use of the public resources in the shape of subsidies to foster farms' productivity.

This research is not free of limitations. The number of observations could be limited to represent Italy, but our sample is the only balanced data useful for panel analysis over the entire period. Another consideration is that for all farms, we normalised all nominal values by hectares without considering the type of farming activity, which might limit the results for breeding farms. A complete assessment of the performance of farms supposed an economic, job, social and environmental analysis; yet, the FADN data lack information regarding jobs, providing insufficient information on environmental issues (e.g., FADN data provide only values and not quantities of pesticides and fertilisers).

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3.6 Technical and economic performance of arable farms in Sweden: does the degree of ecological approaches matter? (SLU)

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3.6.1 Introduction

This case study (CS) report of deliverable D3.1 of the LIFT project presents the results of the technical and economic performance of arable farms in Sweden. The aim of this CS report is to feed D3.1 on farm technical-economic performance depending on the degree of ecological approaches in workpackage (WP) 3 of LIFT.

The analysis is based on FADN data for the period 2010-2016. Two methodological approaches for analysing the technical efficiency (TE) and the economic performance of arable farms in Sweden were used. The TE analysis was based on a stochastic frontier approach, incorporating variables on the degree of ecological approaches and factors driving the TE of the farms. The economic performance of farms was estimated by standard economic indicators of profitability, partial productivity and long-term financial stability and dependence on subsidies.

3.6.2 Description of case study region

Swedish crop production is dominated by cereals and grassland. Climate and production conditions and thereby crop distribution and yields vary across different areas. Yields per hectare are largest in the plain districts. Bread grains are mostly grown in the plain districts of south and central Sweden, whereas in the north, crop production mostly comprises forage and coarse grains. Oilseed production, is also located in the southern and central areas. Potatoes are grown in all parts of Sweden, sugar beets are only grown in the southernmost parts.

The agricultural crop production in Sweden faces several economic and ecological challenges; where, ecological approaches/management practices such as organic farming, crop rotation practices, cultivar mixtures, ploughing/no-tillage and low use of chemicals are among the most common for coping and responding to these challenges. These approaches can be considered individually or in combination.

Compared to the remaining ecological approaches, the promotion of organically certified agriculture is high on the agenda of the Swedish food strategy 2030, both in terms of production and consumption. By 2030, organic farming is targeted to 30 % organically certified area, and 60 % consumption of organic food products within the public sector (Regeringskaseliet, 2018). In Sweden 20 % of the total agricultural area is certified as organic, and there is a constant increasing trend of further convention, both for the agricultural land and pastures (Jordbruksverket, 2020). The national goal set for 2030 of 30 % organically certified area is yet to be achieved.

3.6.3 Methodological approaches

Two methodological approaches for analysing the technical- and the economic performance of arable farms in Sweden were used. Stochastic frontier approach was used for the TE analysis. The analysis incorporated variables on factors driving the technical performance of the farms with a main focus on the degree of ecological approaches. The economic performance of farms was estimated by standard economic indicators of profitability, partial productivity, long-term financial stability and dependence on subsidies.

3.6.3.1 Technical efficiency analysis

3.6.3.1.1 Data and variables

The empirical data used for estimating the TE is an unbalanced panel of data for 215 individual crop farms and a total of 943 observations of arable farms from the Swedish farm accounting data network (FADN) database for the period 2010-2016. The dataset provided detailed information on variables to be used for estimating the TE model for the arable production. Descriptive statistics of variables used for the TE analysis is presented in Table 1.

Table 1: Descriptive statistics of variables included in the technical efficiency analysis (n=5073)

Continuous variables	**Symbol**	**Unit**	**Mean**	**Std. Dev.**	**FADN Definition**
Arable land area	x_1	ha	109.93	105.05	SE025
Labour	x_2	hours	2944.38	3097.1	SE010
Fixed cost	x_3	1000 SEK	774.00	144	SE360 + SE370 + SE375 + SE380
Intermediate cost	x_4	1000 SEK	235.00	379	SE275
Total revenue of agricultural outputs	y	1000 SEK	2274	3448	SE131
Crop diversity index two years before	z3	-	0.79	0.18	
Crop diversity index current year	CDI	-	0.79	0.18	
Herfindahl index	HI	-	0.21	0.18	
CAP subsidy for environmental protection	z1	1000 SEK	84.75	287	FJ0426
CAP subsidy	z2	1000 SEK	337.00	449	SE605
Dummy variables	**Symbol**	**Unit**	**% of 1**	**Obs. no. of 1**	**Obs. no. of 0**
Organic farming (1 = either partly organic production, or fully organic production, or in shift process of organic production; 0 = no organic production at all)	z4	-	8.06	867	76
Main crop change (1 = at least the main crop has been changed in past years, 0 = otherwise)	z5	-	28.1	265	678
Year of policy shock (1 = year later than 2013, 0 = otherwise)	z6	-	28.31	267	676

The crop diversity index in the past two years was calculated using data from 2009 to 2015

In the stochastic frontier production function, we have one output and four inputs (Table 1). The output is represented with total revenue of agricultural outputs (y), which means all farm revenue obtained from the production and agricultural activities. The unit of measurement was 1000 Swedish Kronor (1000 SEK), deflated with the respective national output price index, with 2010 as the base year. Inputs were aggregated as follows: i) the arable land area (x_1), which means utilised agricultural area (UAA) in hectares, including both arable and grazing area; ii) labour (x_2), showing the total labour input including family and hired of the farm, expressed in total working hours; iii) fixed costs (x_3), which is represented by the total costs of capital use, including: depreciation, maintenance of buildings and machinery, rents and insurance; iv) intermediate cost (x_4), which includes total costs of seeds, fertilisers, crop protection, feed, energy and other specific costs. The inputs given in value units (material and capital costs) were measured in 1000 SEK, deflated with the respective national input price index (base year 2010). Information on the national output price and input price index was obtained from the Swedish Board of Agriculture (Swedish Board of Agriculture 2015).

The determinants of technical inefficiency were explained in the lower part of Table 1. The first possible technical inefficiency determinant variable was the variable of **CAP subsidy for environmental protection** (z_1). The **other subsidy** (z_2) was also introduced in the technical inefficiency model.

We also investigated **how the degree of ecological approaches is associated with TE** of crop production. The degree of ecological approaches was represented by three variables: i) crop diversity index in the past two years (z_3); ii) organic farming (z_4) and iii) crop rotation (z_5). In Sweden, organic farming, crop rotation and cultivar mixtures practices, are among the most common ecological approaches for coping and responding to environmental challenges. In regard to the LIFT farm typology, organic farming is clearly represented. In addition, crop rotation is a common practice for agroecology, integrated farming and conservation agriculture, and diversification/polyculture is common for agroecology (Rega et. al, 2018).

We calculated the CDI through the equation $CDI = 1 - HI$, where HI is the the **Herfindahl index**. HI is defined as equation $HI = \sum_{i=1}^{n} P_i^2$, where P_i is the proportion of area planted by the crop i, $P_i = \frac{A_i}{\sum_{i=1}^{n} A_i}$, A_i is the area of the crop i, i is each of the crops such as ley, barley, wheat, oat etc. In the literature, e.g. Smale et al. (2008) Herfindahl index has been used to capture the area distribution of varieties. A Herfindahl value of 1 indicates the farm planted a single crop while a value of 0 indicates that a large number of crop varieties were planted in the farm. HI can be calculated from the FADN dataset, and then we can get CDI and CDI lagged in past two years. The CDI is directly related to the diversification in the farm by taking into account the area size of each crop, it ranges with the value between 0 and 1, the greater the number of CDI, the higher degree of crop diversification. Whereas, the greater the number of HI, the higher the monoculture in the arable land.

Crop rotation is alternating annual crops grown on a specific field in a planned pattern or sequence in successive crop years, for improving the soil quality. Because we cannot derive the position of a specific crop in an individual farms from the FADN database, we instead investigate the main crop change to reflect the practice of crop rotations. Main crop means the crop planted with the largest planting area in our sample. As listed in Table 2, for the sample included in the analysis the largest crops planted are ley, wheat and corn. Ley is planted with 45.39% of arable land area, following by cereals (wheat and corn with land area of 19.72% and 17.6% respectively). The second largest crops planted are beet, corn and oat. They are planted with 22.4%, 19.94%, and 12.97% planted areas respectively. As listed in Table 1, the mean of main crop change is 0.281, which means 265 observations out of 943 observations had rotated the main crop planted.

Table 2: Main crops planted in Sweden

Code in FADN	Crop	% of total arable land area
The largest planted crops		
FK1161	ley	45.39
FK0491	wheat	19.72
FK0521	corn	17.6
The second largest planted crops		
FK1191	beet	22.4
FK0521	corn	19.94
FK0531	oat	12.97

The third variable representing an ecological approach is **organic farming** (z_4). We have the dummy variable of organic farming to be either 1 or 0, whereas 1 means the farm had either partly organic production, or fully organic production, or it was in the shift process to organic production. 0 meant the farm was not organic at all. The mean of organic farming was 0.081, which indicated major observations are relevant to no organic farming at all in the sample.

The last technical inefficiency determinant is **year of policy shock**, with that we want to see how policy change affected the production performance. There was the Common Agricultural Policy (CAP) reform in 2013, when **the mandatory greening component of direct payments** was introduced to promote sustainable land use (European Union, 2013). So we generated a dummy assigned with 1 to show period after the policy change, when the year was later than 2013, and 0 otherwise.

3.6.3.1.2 Stochastic frontier approach

The parametric Stochastic Frontier Approach (SFA) (Aigner et al. 1977; Meeusen and Broeck 1977), conducted in STATA, was applied. SFA estimates farm TE by measuring the distance between the observed and "best" feasible input-output combination of farms given the highest possible amount of output/revenue that can be obtained (while keeping the amount of inputs fixed), i.e. it is an output-oriented approach (Coelli et al. 2005). Where balanced panel data are available, models for panel data are preferable and can be expected to control for unobserved differences between observations, capturing the 'firm effect' and adding a time dimension to the analysis (Fried et al. 2008; Parmeter and Kumbhakar 2014). However, the present analysis was based on a rotating unbalanced panel dataset where, with large numbers of farms that appeared for a period shorter than three years, pooled data model was deemed as more appropriate. The Trans-log production function was selected after we tested and compared the Trans-log production function and Cobb-Douglass production function, details of the test were displayed in Table 4 in the results section.

The Trans-log stochastic frontier production function equation (1) specification was as follows:

$$lny_i = \alpha_0 + \sum_{k=1}^{4} \beta_k lnx_{ik} + \frac{1}{2}\sum_{k=1}^{4}\sum_{l=1}^{4} \beta_{kl} lnx_{ik} lnx_{il} + v_i - u_i \qquad (1)$$

In the Trans-log stochastic frontier production function the output of farm revenue y_i obtained for the i^{th} farm is a function of the inputs x_i used in the production process; ln denotes the natural logarithm; α_0 is a constant term; β and γ are parameters to be estimated; v_i is random noise, independently and identically distributed $N(0,\ \sigma_v^2)$; and u_i an inefficiency term. In the empirical specification of Translog production function, we have one output of total revenue of agricultural outputs and four inputs x_1 of arabland area, x_2 of labour, x_3 of fixed costs and x_4 of the intermediate cost.

In a stochastic frontier model with output-oriented specification, the inefficiency term u_i represents the log difference between the maximum attainable output and the actual output (Kumbhakar et al. 2015). For equation (1), $u_i = lny_i^* - lny_i$ and the inefficiency term is then: $\exp(-u_i) = \frac{y_i}{y_i^*}$. Since the observed output is bounded below the frontier output level (the maximum attainable output), $u_i \geq 0$ and the value of the estimated TE coefficient ranges between 0 and 1, denoting farm TE of between 0% and 100%.

The inefficiency variance function (Battese and Coelli 1995) in equation (3) is explained by z_i, the vector of variables associated with the inefficiency sources; δ, the parameter to be estimated and w_i, which are the unobservable random variables, assumed to be independently distributed and obtained by truncation of the normal distribution with zero mean and unknown variance σ_w^2, such that $u_i \geq 0$.

$$u_i = z_i^e \delta_i + w_i \tag{2}$$

The constant α in equation (1) and the parameters β, γ and δ in equations (1)-(2) were estimated simultaneously, thereby excluding the possibility of producing biased results with the two-step approach (Wang and Schmidt 2002). In the empirical model, we have 7 inefficiency determinants z_1 of CAP subsidy for environmental protection (z_1), which was represented by the code FJ0426 in FADN dataset, z_2 of the other subsidy, z_3 of crop diversity index in past two years, z_4 of the degree of diversification/crop rotation in terms of crops, z_5 of the organic farming, and z_6 for year of policy shock.

3.6.3.1.3 Indicators of economic farm performance

Data for farms specialising in arable production were used. Farm selection was based on the standard FADN typology for farm specialisation. The empirical data used for estimating the economic performance of farms is an unbalanced panel of 989 observations of arable farms from the Swedish farm accounting data network (FADN) database for the period 2010-2016.

The economic performance of farms was estimated with standard economic indicators of profitability, partial productivity, and long-term financial stability and dependence on subsidies. Profitability indicators represent the revenue cost ratios (i.e. revenue indicator / cost indicator), where a ratio > 1 means a farm can cover all costs. Partial productivity indicators show the average number units of output are produced by one unit of a respective input. Indicators of economic farm performance, with respective definitions are summarised in Table 3.

Table 3: Definitions of indicators of economic farm performance

Name	Description	Definition in FADN
Profitability indicators		
Private revenue-cost-ratio not considering remuneration of owned production factors	Revenue / (intermediate expenses+ depreciation + paid interest + paid labour + paid rent). Expresses ability of a farm to cover costs, not having to cover costs for owned production factors, with its private revenues.	SE131 / (SE275 + SE360 + SE370 + SE375 + SE380)

Public revenue-cost-ratio not considering remuneration of owned production factors	(Revenue + subsidies) / (intermediate expenses + depreciation + paid interest + paid labour + paid rent). Expresses ability of a farm to cover costs, not having to cover costs for owned production factors, with its private revenues and public subsidies	(SE131 + SE605) / (SE275 + SE360 + SE370 + SE375 + SE380)
Private revenue-cost-ratio considering remuneration of owned production factors	Revenue / (intermediate expenses + depreciation + (assets * imputed interest rate) + (total labour in hours * imputed wage per hour) + (land * imputed rent)) Expresses ability of a farm to cover all costs, including those for owned production factors with its private revenue	SE131 / SE275 + SE360 + (SE436 * imputed interest rate) + (SE011 * imputed wage per hour) + (SE025 * imputed rent per ha)
Public revenue-cost-ratio considering remuneration of owned production factors	(Revenue + subsidies) / (intermediate expenses + depreciation + (assets * imputed interest rate) + (total labour in hours * imputed wage per hour) + (land * imputed rent)) Expresses ability of a farm to cover all costs, including those for owned production factors with its private revenue and public subsidies	(SE131 + SE605)/ SE275 + SE360 + (SE436 * imputed interest rate) + (SE011 * imputed wage per hour) + (SE025 * imputed rent per ha)
Partial productivity indicators		
Average product of land	Partial productivity indicator, describing output per unit of the input land	SE131 / SE21 Output / land
Average product of labour	Partial productivity indicator, describing output per unit of the input labour	SE131/SE010 Output / labour in AWU
Average product of assets	Partial productivity indicator, describing output per unit of the input assets	SE131/SE436 Output / assets
Average product of intermediary expenses	Partial productivity indicator, describing output per unit of the input intermediary expenses	SE131/SE275 Output / intermediary expenses
Additional indicators		
Market orientation	Revenue / (Revenue + subsidies) Describes how much a farm relies on public subsidies, compared to private revenues	SE131 / (SE131 + SE605)
Equity ratio	Equity / total assets Share of the assets financed by the farmers.	SE501 / SE436

3.6.4 Results and discussion

In this section, we present the results of the two analytical approaches, i.e. the TE analysis and the standard economic indicators of profitability, productivity, long-term financial stability and farm dependence on subsidies.

3.6.4.1 Analysis on technical efficiency performance of the arable farms in Sweden

3.6.4.1.1 Hypothesis tests and production function selection

Table 4 provides results on the hypothesis tests for model specification and statistical assumptions. Before deciding on the specifications for the final version of the model we first tested the hypothesis for the model specification and variable selection, e.g. whether to choose a Cobb-Douglass production function or Translog production function and how variables in the technical inefficiency model are selected. The test 1 and test 2 were designed to test whether the Cobb-Douglass production function or the Translog production function fits better. According to the Likelihood Ratio (LR) test, we can see either in Test 1 or in Test 2, that the Translog production function fitted the data better than Cobb-Douglass production function statistically significantly.

LR tests were also applied to examine the effect of ecological approaches on technical inefficiency. The null hypothesis states that ecological approaches had no effect on technical inefficiency. Test 3 indicated that z_1 of CAP subsidy for environmental protection and $z_2$of the other subsidy had no effects on the technical inefficiency. Test 4 indicated that z_3 of crop diversity index in the past two years had no effects on the technical inefficiency. Test 5 indicated that z_4 of the degree crop rotation had no effects on the technical inefficiency, Test 6 indicated that z_5 of the organic farming did not affect the technical inefficiency, as well as the Test 7 for the year of policy shock. The LR tests results rejected all above null hypothesis, which confirmed that variable represented the ecological approaches should be considered in the technical inefficiency model.

Table 4: Hypothesis tests for model specification and statistical assumptions

Test	Null hypothesis	Log-likelihood value	D.F.	AIC	BIC
For selection of production function					
1	H0: Cobb-Douglass production function without technical inefficiency model	-367.4282	7	748.8563	782.7998
	H1: Translog production function without technical inefficiency model	-356.0229	17	746.0457	828.4798
2	H0: Cobb-Douglass production function with technical inefficiency model	-326.9812	13	679.9625	743.0003
	H1: Translog production function with technical inefficiency model	-317.8008	23	681.6017	793.1302
For specification of technical inefficiency model					
	H1: Unlimited model	-317.8008	23	681.6017	793.1302
3	H0: $\omega_1 = \omega_2$ =0	-348.3794	21	738.7589	840.5893
4	H0: ω_3 =0	-321.2311	22	686.4622	793.1416
5	H0: ω_4 =0	-318.8712	22	681.7423	788.4218
6	H0: ω_5 =0	-317.9999	22	679.9997	786.6792
7	H0: ω_6 =0	-320.1952	22	684.3904	791.0699

3.6.4.1.2 Estimates for the stochastic production function

Maximum likelihood estimates of the stochastic production function were presented in Table 4. In order to facilitate the interpretation of the parameter estimates, the output variable and the four input variables were divided by their respective sample means. Hence, the estimated first-order parameters of the Translog production function can be interpreted as partial production elasticities at the sample mean (Glauben et al., 2002).

Model 1 is the production function without specifying the technical inefficiency, which were detailed estimates for the hypothesis H1 of Test 1 in Table 4. In Model 1, the sigma_u is estimated to be 0.545, which was larger than 0.5, meaning that the variance in the farm specific error term was greater than the variance in the stochastic error term. This result revealed that the one-sided random inefficiency component dominates the measurement error and other random disturbances, in other words, that meant the technical inefficiency model should not be ignored.

Model 2 is the final model specification of the production function complete with the technical inefficiency model, which was exactly the hypothesis H1 for Test 2 - 7. The overall model quality seems satisfactory, according to both likelihood ratio tests and statistics.

The Model 3 was designed to see how the ecological approaches affected the performance of the model, where all the ecological approaches were excluded in the Model 3. Almost all first order and second order coefficients of the inputs had the expected sign, except the first order parameter estimated for input of fixed cost, and estimated results meet the regularity conditions (Morey, 1986).

The estimates from Model 1 to Model 3 were consistent, so we focused on explaining the results in Model 2. The first order and second order estimates of input cropland area and fix cost were not statistically significantly. The labour and intermediate input cost were estimated positively significantly at the 1% level. When considering the magnitude of partial elasticity at the sample mean, inputs of labour and intermediate cost were important for crop production. A partial production elasticity of 0.131 was observed for labour, meaning that a 1% increase of labour will increase crop production by 13.1%. The biggest partial production elasticity came from intermediate input and was 0.810 significance at the 1% statistical level that indicated intermediate inputs were the most important for the crop production in Sweden.

3.6.4.1.3 Estimates for the technical inefficiency model and the effects of ecological approaches

The determinants for the variation of a farm technical inefficiency were estimated in the technical inefficiency model (lower part of Table 5). Because technical inefficiency was the dependent variable in the technical inefficiency model, a negative parameter coefficient for the variables indicated a negative effect on technical inefficiency, but a positive effect on TE.

CDI in lagged two years was estimated to be positively correlated with TE. This is consistent with the literature, where higher crop diversity contributes to increasing the productivity (Cardinale et al. 2012). Crop diversity stabilised its crucial role in agricultural production, with higher crop diversity improving the crop production; in particular the productive value of biodiversity that crop diversity increases crop yields has been emphasised (Bareille and Letort 2018). However, the estimate of organic farming indicated that the organic farming approach is negatively related with TE. Although the estimates of organic farming and crop rotation were not statistically significant in Model 2, the test of excluding organic farming and crop rotation approach indicated the crop rotation approach was important for the whole model specification.

The total amount of CAP subsidy was found to be positively related with the TE. The policy shock introduced in 2014 was found to be negatively related with the TE, emphasising that complying with the “greening” requirements required additional farm resources to be used.

Table 5: Estimates of the stochastic frontier model

Variables	parameters	Model 1		Model 2		Model 3	
		Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Dependent variable: *ln(y)* of Translog production function							
Constant	α_0	0.392***	0.019	0.335***	0.019	0.340***	0.019
ln(x_1)	β_1	-0.008	0.018	-0.005	0.016	-0.002	0.016
ln(x_2)	β_2	0.122***	0.031	0.131***	0.026	0.127***	0.027
ln(x_3)	β_3	-0.024	0.040	-0.034	0.036	-0.035	0.036
ln(x_4)	β_4	0.845***	0.048	0.810***	0.042	0.815***	0.042
0.5ln(x_1)^2	β_{11}	-0.002	0.005	-0.001	0.004	-0.002	0.004
0.5ln(x_2)^2	β_{22}	-0.072	0.065	-0.038	0.064	-0.033	0.065
0.5ln(x_3)^2	β_{33}	0.025	0.024	0.018	0.026	0.016	0.026
0.5ln(x_4)^2	β_{44}	0.246***	0.075	0.215***	0.073	0.206***	0.072
ln(x_1) ln(x_2)	β_{12}	0.047*	0.025	0.044*	0.025	0.042*	0.025
ln(x_1) ln(x_3)	β_{13}	0.005	0.017	0.011	0.017	0.013	0.017
ln(x_1) ln(x_4)	β_{14}	-0.031	0.027	-0.037	0.026	-0.040	0.026
ln(x_2) ln(x_3)	β_{23}	0.039	0.026	0.029	0.030	0.025	0.030
ln(x_2) ln(x_4)	β_{24}	-0.049	0.048	-0.043	0.047	-0.042	0.047
ln(x_3) ln(x_4)	β_{34}	-0.112***	0.037	-0.094**	0.038	-0.088**	0.038
Technical inefficiency model, dependent variable: technical inefficiency relevant							
Constant	ω_0	-1.179***	0.071	-1.716***	0.113	-1.692***	0.106
ln(z_1)	ω_1			0.001	0.007	0.002	0.007
ln(z_2)	ω_2			-0.574***	0.080	-0.533***	0.078
ln(CDI_lag2)	ω_3			-0.100**	0.042		
Organic farming	ω_4			0.118	0.190		
Crop rotation	ω_5			-0.172	0.117		
Year of policy shock	ω_6			0.279**	0.128	0.307**	0.126
Vsigma							
Constant		-3.594***	0.141	-3.679***	0.131	-3.693***	0.132
sigma_u		0.554***	0.020				
sigma_v		0.166***	0.012	0.159***	0.010	0.158***	0.010
lambda		3.345***	0.027				
Log likelihood		-356.0229		-317.8008		-322.3624	
Number of observation		943		943		943	
Wald chi2(14)		9129.85		7909.57		7867.27	
Prob > chi2		0.0000		0.0000		0.0000	

*Significant at 10% level (P < 0.10), **Significant at 5% level (P < 0.05), ***Significant at 1% level (P < 0.01)

3.6.4.1.4 Summary of technical efficiencies

After estimation of the stochastic production function and technical inefficiency model, we calculate the TE for each farm based on Model 2. Table 6 shows the summary statistics of the TE scores. The average estimated TE for farms in Sweden was 0.692, indicating that on average, farms produced 69.2% of the potential output given the present state of technology and the input level. Therefore, the possibility of increasing crop production by an average of 30.8% can be achieved in the short term by adopting the practices of the best performing farms. About 14.42% of farms had a TE score smaller than 0.50, whereas 11.45% of farms had TE scores greater than 0.50 and less than or equal to 0.60, and 19.19% of farms had TE scores greater than 0.60 and less than or equal to 0.70. About 22.38% of farms had TE scores more than 0.70 and less than or equal to 0.80, 26.94% of the farms had TE scores more than 0.80 and less than or equal to 0.90, and only 5.62% of farms operated with a TE score greater than 0.90.

Table 6: Summary statistics of technical efficiency (TE)

Variable	Obs	Mean	Std. Dev.	Min	Max
Overall TE	943	0.692	0.172	0.011	0.962
TE in southern Sweden	876	0.703	0.161	0.077	0.962
TE in northern Sweden	67	0.556	0.238	0.011	0.898
Distribution	**Farm observations**		**Percentage**		
TE<0.5	136		14.42		
0.5≤TE<0.6	108		11.45		
0.6≤TE<0.7	181		19.19		
0.7≤TE<0.8	211		22.38		
0.8≤TE<0.9	254		26.94		
TE>0.9	53		5.62		

The normal- kernel density distribution of TE in Sweden is presented in Figure 1.

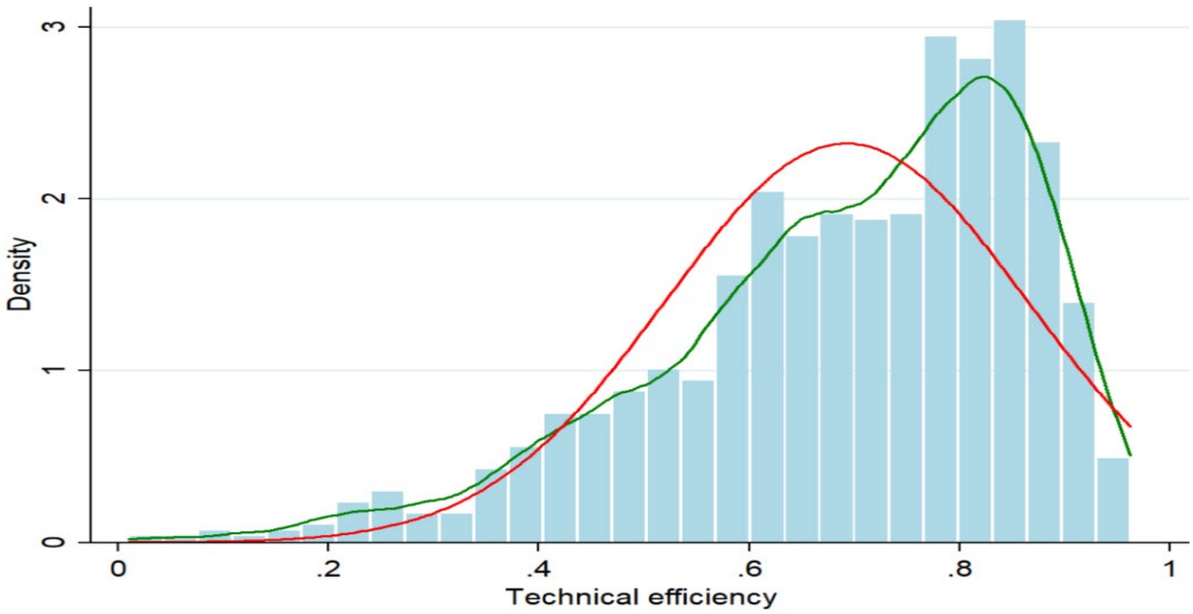

Figure 1: Histogram graphs of TE in southern (green line) and northern (red line) Sweden

3.6.4.2 Analysis on standard indicators of economic performance of the arable farms in Sweden

Descriptive statistics of the indicators of economic performance is given in Table 7. Swedish arable farms are dependent on subsidies. The average dependence on subsidies is 18% for conventional and 22% for organic farms. Without considering the public support Swedish arable farms applying conventional and organic approaches can on average cover 97% respective 85% of the costs excluding costs for owned production factors. The farm revenue can cover on average 9% vs. 11% of the costs of owned production factors, for the conventional and the organic farms respectively. Conventional farms cover on average 74% of the assets, respective 65% for the organic farms. Conventional farms have on average larger value of average product of land and intermediary costs, whereas organic farms are better-off in terms of the average product of labour, and have slightly higher average value for the average product of capital.

Table 7: Descriptive statistics of the economic performance indicators (n=989)

Economic performance indicator	**Sample mean**	**Ecological approach**	
		Conventional mean	**Organic mean**
Profitability indicators			
Private revenue-cost-ratio excluding owned production factors	.96	.97	.85
Public revenue-cost-ratio excluding owned production factors	1.17	1.18	1.09
Private revenue-cost-ratio including owned production factors	.09	.09	.11
Public revenue-cost-ratio including owned production factors	.11	.11	.13
Partial productivity indicators			
Average product of land	1470.52	1476.82	1403.45
Average product of labour	159695.90	158337.80	174140.30
Average product of capital	.23	.22	.28
Average product of intermediary expenses	1.39	1.40	1.30
Additional indicators			
Market orientation	.82	.82	.78
Equity ratio	.73	.74	.65

Note: SEK is for the Swedish currency kronor; where 10.SEK = 0.9 euro.

3.6.5 Conclusions

In this CS report deliverable, we have presented the results of the technical and the economic performance of arable farms in Sweden. Based on FADN data for the period 2010-2016, two methodological approaches for analysing the TE and the economic performance of arable farms in Sweden were used. The TE analysis incorporated variables on the degree of ecological approaches and factors driving the TE of the farms. The economic performance of farms was estimated by standard economic indicators of profitability, partial productivity and long-term financial stability and dependence on subsidies.

The average estimated TE for farms in Sweden was 0.692 indicating a possibility for increase in the crop production value by an average of 30.8%, by adopting the practices of the best performing farms. Discrepancies in the TE level were identified in regard to the location; where farms in southern Sweden were found to be on average technically more efficient than the farms located in northern Sweden, i.e. 70.3% vs 55.6%. The largest partial production elasticity was estimated for the intermediate input (0.810 significance at the 1% statistical level) indicating that the intermediate input was the most important input for crop production. The analysis on the determinants of a farm TE showed a positive impact of both the CAP subsidy and a mixed effect of ecological approaches, the CDI in lagged two years was estimated to be positively correlated with TE, but organic farming approaches and crop rotation approach were estimated not significantly correlated with TE.

For most of the indicators of economic performance conventional farms are better-off or have similar average score with the organic farms. Conventional farms cover a larger share of costs for farms production factors excluding owned factors i.e. 97% vs 85% for the organic farms. When owned factors are included, the coverage is 9% vs. 11% for the conventional and the organic farms. The value of average product of land and intermediary costs are on average larger for the conventional farms, whereas, organic farms are better off in terms of the average product of labour and slightly on capital. Swedish arable farms are dependent on subsidies. Subsidies' contribution to the total farm income is on average 18% for the conventional and 22% for organic farms. Conventional farms cover on average 74% of the assets, respective 65% for the organic farms.

The economic performance of farms located in North Sweden, and of organic farms is lower when subsidies are not considered, signalling for the need that the losses originating from regional production potential, and from applying organic farming approaches need to be compensated.

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3.7 Comparison of total factor productivity and its components between low input and conventional farming systems: the case of Hungarian cereal oilseed and protein (COP) crop producing farms (2011-2015) (MTA KRTK)

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3.7.1 Introduction and description of case study region

The aim of this paper is to compare total factor productivity (TFP) and its components of Hungarian low input and conventional Cereals, Oilseed and Protein (COP) crop producing farms (according to the FADN *types of farm* classification (TF14), farms with group identifier: 15).

Ecological approaches to farming practices are gaining interest across Europe. As this interest grows there is a pressing need to assess the potential contributions these practices may make and their attractiveness to farmers as potential adopters. In this paper we compare differences in TFP and its components of low input and conventional farming systems.

Assignment to the farming systems is based on the protocol that was developed within the LIFT project (Rega et al., 2019).

The description of the case study region can be found in Barath et al, 2021 (Differences in Efficiency and Productivity between conventional and organic farms: the case of Hungarian Cereal Oilseed and Protein (COP) crop producing farms (2010-2015**)**.

First, we estimate Stochastic Frontier Models to examine production technology and technical efficiency (TE) of farms. In order to consider differences in production technology we apply a random parameter stochastic frontier model. Second, based on the estimated parameters we construct transitive Törnquist-Theil total factor productivity (TFP) index, which enable multilateral comparison of farms or group of farms. Then we decompose this index into differences in technological change, technical efficiency and scale efficiency. We use statistical tests to examine whether the differences between low input and conventional farms are statistically significant.

The structure of the paper is as follows. In the next section, we describe the database and variables used for the analysis. It will be followed by the description of the applied methodology then we report the results and discussion of the results, finally we conclude.

3.7.2 Data

For the empirical analysis, we used data from the EU Farm Accountancy Data Network (EU FADN). We used a balanced panel over the 2011-2015 period. After cleaning the data the total number of farms was 2655, we had 2441 conventional farms and 214 low input farms.

Descriptive statistics of the applied variables can be found in Table 1. For the purpose of production frontier estimation, one output (Y – total agricultural production in value) and four inputs (labour in Annual Work Units (X_1), utilised agricultural area (UAA) in hectares (X_1), total fixed assets in value (X_2) and total intermediate consumption in value (X_3) were used. Additionally, a time variable (t) and time-squared variable (tt) were added to the production frontier to allow for non-monotonic technical change.

Over the estimation all of the variables expressed in nominal prices were deflated to 2010 prices with the use of the appropriate deflators reported by the Hungarian Central Statistical Office (HCSO); precisely the output was deflated by the agricultural output price index, the intermediate consumption by the price index of purchased goods and services and the corresponding values of total fixed assets by the price index of agricultural investments.

Table 1: Descriptive statistics

	Conventional				
	Mean	**Standard Deviation**	**Minimum**	**Maximum**	**Observation**
Output(Y)	233023.60	375562.00	3.58	3851833.00	2441.00
LABOUR (X_1)	3.60	6.63	0.01	76.65	2441.00
LAND (X_2)	239.32	343.74	6.51	2823.81	2441.00
Capital (X_3)	327606.50	354849.80	242.47	2675589.00	2441.00
Materials (X_4)	19445.95	29677.16	164.69	452780.10	2441.00
	Low Input				
Output(Y)	85688.20	142717.10	3916.08	1708134.00	214.00
LABOUR (X_1)	1.40	2.12	0.02	12.72	214.00
LAND (X_2)	141.75	230.96	7.20	2366.00	214.00
Capital (X_3)	134407.40	176698.90	939.58	1190739.00	214.00
Materials (X_4)	6914.74	10455.89	48.59	107980.40	214.00
	All farms				
Output(Y)	221148.00	364578.90	3.58	3851833.00	2655.00
LABOUR (X_1)	3.42	6.42	0.01	76.65	2655.00
LAND (X_2)	231.46	337.07	6.51	2823.81	2655.00
Capital (X_3)	312034.10	347905.30	242.47	2675589.00	2655.00
Materials (X_4)	18435.90	28812.03	48.59	452780.10	2655.00

Source: Own calculation based on FADN data

3.7.3 Method

First, we estimate production structure and technical efficiency. We model production technology with an SFA model. Traditional frontier models assume that all firms face common technology. However, in practice firms use different technologies for a variety of reasons (Tsionas, 2002).

As the main goal of this paper is to compare low input and conventional farms and these group of farms certainly use different technologies we apply a Random Parameter Model (RPM) which allow us to consider technological differences among farms.

The RPM, following Greene (2005), may be written as follows:

$$y_{it} = \alpha_i + \boldsymbol{\beta}_i'\boldsymbol{x}_{it} + \beta_{ti}t + v_{it} - u_{it}, \quad (1)$$

where

$$v_{it} \sim N[0, \sigma_v^2],\ v_{it} \perp u_{it}$$
$$u_{it} = |U_{it}|, U_{it} \sim N[0, \sigma_u],$$
$$\alpha_i = \bar{\alpha} + \alpha_w w_i,$$
$$\boldsymbol{\beta}_{xi} = \overline{\boldsymbol{\beta}}_x + \boldsymbol{\beta}_{xw} w_i,$$
$$\beta_{ti} = \bar{\beta}_t + \beta_{tw} w_i, \text{ where}$$

, i=1,…,N indicating the number of farms; t=1,…,T indicating the time period, w is an unobservable latent random term; $\alpha_i, \boldsymbol{\beta}_{xi}, \beta_{ti}, \alpha_w, \boldsymbol{\beta}_{xw}, \beta_{tw}$ denote the parameters to be estimated, u_{it} represents technical inefficiency, and v_{it} stands for statistical noise (Greene, 2005). y_{it} represents the output variable and $\boldsymbol{x}_{it}$ are inputs.

Third, based on the estimated parameters of the RPM, we constructed multilateral-consistent Törnquist-Theil TFP index (Caves et al., 1982). This productivity index between farm i in period t and the sample average can be formulated as follows:

$$\ln \mathrm{TFP}_{it}^{TTI} = \left(\ln y_{it} - \overline{lny}\right) - \frac{1}{2}\sum_k (S_{kit} + \overline{S_k})\left(\ln x_{kit} - \overline{\ln x_k}\right) \quad (2)$$

, where $k = 1, \ldots, K$ inputs; and S stands for share of inputs. A bar above a variable refers to the arithmetic mean of the variable over all sample observations.

Fourth, we decomposed the TFP index. The estimated TFP index can be decomposed into an effect which results from adjustments in the scale of factor use (SE), a technological change effect (TCH), and changes in TE (TE), i.e.:

$$\mathrm{TFP} = \mathrm{TCH} \times \mathrm{TE} \times \mathrm{SE}. \quad (3)$$

Finally, we used statistical tests to compare the differences between low input and conventional farms in TFP and its components.

3.7.4 Results

3.7.4.1 Parameter estimates of the Random Parameter Model

Selected parameter estimates of the estimated Translog production SF Model are presented in Table 2.

The results show that all of the first order coefficients are statistically significant and have the expected sign (positive), i.e. monotonicity criteria that is suggested by production theory is satisfied. We conducted several tests before choosing this model.

First, we tested Translog against Cobb-Douglas functional form using Likelihood ratio test. The test clearly rejected Cobb Douglas functional form.

Next, we compared, traditional Normal/Half-Normal SFA model (where the effect of heterogeneity is not accounted for), True random effect Model (where heterogeneity affect only the intercept) with RPM (where heterogeneity affect not only the intercept, but all of the input variables, i.e. it has an effect on marginal productivity of all of the inputs) based on Akaike Information Criteria (AIC). The test clearly showed that RPM fit better to this data.

Table 2: First order coefficient of the estimated RPM

	Coefficients	Standard Error	z	Prob |z|>Z*	95% confidence interval	
Constant	0.21076***	0.011	19.870	0.000	0.190	0.232
Time	-0.01041**	0.004	-2.520	0.012	-0.019	-0.002
Labour	0.11454***	0.009	13.360	0.000	0.098	0.131
Land	0.63155***	0.017	37.990	0.000	0.599	0.664
Capital	0.13233***	0.006	20.460	0.000	0.120	0.145
Materials	0.18637***	0.014	12.920	0.000	0.158	0.215

Moreover, results show to some extent a higher estimate for land and lower for material compared to estimates for different time periods. Therefore, we checked the robustness of these results, other models showed similar results confirming that over the analysed period the elasticity of land is higher and the elasticity of material is lower over this time period on the case of balanced panel.

According to the results land was the most and labour was least influential input. Interestingly, the estimate of technological change is negative. One possible explanation for this negative sign is that technological change measured in this way does not measure purely the changes in technology, it is combined measure of technical and environmental change that is the negative sign is might be a consequence of worsening weather condition. However, further research is needed to examine the effect of weather on the production, but this is out of the scope of this paper.

3.7.4.2 Comparison of TFP and its components

Table 3 shows the results of TFP decomposition. It can be seen that the TFP for conventional farms are much higher compared to Low input farms. The reason of this difference is the higher technical and scale efficiency of conventional farms. All these results are highly statistically significant according to Mann-Whitney test, the associated p-value id 0.000. Technological change was similar for both farms.

Table 3: Decomposition of the TFP index

	Mean	Std. Dev.	Min	Max
TFP				
Conventional	1.03	0.20	0.35	2.45
Low Input	0.91	0.16	0.45	1.37
Mann-Whitney Test: Prob > |z|	0.000	-	-	-
TCH				
Conventional	1.00	0.06	0.92	1.17
Low Input	1.00	0.06	0.93	1.17
Mann-Whitney Test: Prob > |z|	0.000	-	-	-
SE				
Conventional	1.01	0.13	0.56	1.81
Low Input	0.94	0.07	0.63	1.15
Significance		-	-	-

	TE			
Conventional	1.01	0.12	0.50	1.23
Low Input	0.96	0.14	0.54	1.20
Mann-Whitney Test Prob > |z|	0.000	-	-	-

Source: Own calculation based on FADN data

3.7.5 Conclusions

The aim of this paper was to compare total factor productivity (TFP) and its components of Hungarian low input and conventional Cereals, Oilseed and Protein (COP) crop producing farms. We identify low input farms based on the protocol that was developed within the LIFT project.

First, we estimate production technology and technical efficiency using a random parameter stochastic production frontier model, which allow us to consider technological differences among farms. Then we calculate and decompose Törnquist-Theil TFP index into its components.

We compare the differences between Low input and conventional farms using statistical tests. Results show that TFP scores of low input farms are smaller compared to conventional farms, and the difference is statistically significant.

Technological change is similar for both group of farms, however both technical and scale efficiency score is significantly lower for low input farms.

Results have implications for policy. As the difference between low input and conventional farms was significant in TE and scale efficiency, it suggests that the performance of these farms can be increased with appropriate policy measures. TE might be increased with special agricultural training for low input farm managers. Scale efficiency is sensitive to policies regarding taxes. Reconsideration of agricultural tax policies might improve scale efficiency of low input farms.

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3.8 Differences in efficiency and productivity between conventional and organic farms: the case of Hungarian cereal oilseed and protein (COP) crop producing farms (2010-2015) (MTA KRTK)

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3.8.1 Introduction

The aim of this paper is to compare efficiency and productivity of Hungarian organic and conventional field crop producing farms. More precisely, according to the FADN types of farm classification (TF14), we analyse farms, which are classified as specialists Cereals, Oilseed and Protein (COP) crop producing farms (Grouping Nr. 15 in the TF14 classification system).

3.8.2 Description of the case study area

Field crop production has traditionally been a key sector in Hungarian agriculture. About 40% of all Hungarian farms specialise in field crop production, and use 60% of the arable land and account for more than a third of the output of agricultural production (Pesti and Keszthelyi, 2010). This is the sub-sector of Hungarian agriculture that integrates well with international commerce, in that the product channels are well organised and the products comprise the largest proportion of agricultural exports (Pesti and Keszthelyi, 2010).

For purposes of empirical examination, we use Hungarian national FADN Data over the 2010-2015 period.

First, we estimate Stochastic Frontier Models to examine production technology and technical efficiency (TE) of farms. In order to consider differences in production technology we apply a random parameter stochastic frontier model. Second, based on the estimated parameters we construct transitive Törnquist-Theil total factor productivity (TFP) index, which enable multilateral comparison of group of farms. Third, to eliminate potential selections bias between the analysed groups of farms we compare the TE and TFP scores of organic and conventional farms applying propensity score matching.

The structure of the paper is as follows. In the next section, we describe the database and variables used for the analysis. It will be followed by the description of the applied methodology then we report the results and discussion of the results, finally we conclude.

3.8.3 Data

For the empirical analysis, we used data from the Hungarian Farm Accountancy Data Network (FADN). The Hungarian FADN system contains data from about 1900 annually reporting agricultural farms. For the purpose of estimation, one output (Y – total agricultural production in value) and four inputs (labour in Annual Work Units (X_1), utilised agricultural area (UAA) in hectares (X_1), total fixed assets in value (X_2) and total crop specific costs consumption in value (X_3) were used. Additionally, a time variable (t) and time-squared variable (tt) were added to the production frontier to allow for non-monotonic technical change.

All of the variables expressed in nominal prices were deflated to 2010 prices with the use of the appropriate deflators reported by the Hungarian Central Statistical Office (HCSO); precisely the output (Y) was deflated by the agricultural output price index, the intermediate consumption (X_4) by the price index of purchased goods and services and the corresponding values of total fixed assets (X_3) by the price index of agricultural investments.

We used a balanced panel, in order to ensure the comparison between the same farms over the years analysed. The total Number of COP producing farms was 3000 over the analysed period. The number of organic farms was low; we had only 6 organic farms. The number of conventional farms was 2968; 6 firms was converting to organic production methods and 20 farms applied both organic and conventional production method. Descriptive statistics of the variables are included in Table 1.

The variance is high for all of the variables, suggesting that heterogeneity plays an important role in the case of Hungarian COP producing farms and therefore it is important to account for it in the production model.

Table 1: Descriptive statistics

		Conventional			
	Mean	**Standard Deviation**	**Minimum**	**Maximum**	**Observation**
Output(Y)	200619.6	315238.9	687.4	3664902.0	2968
LABOUR (X_1)	3.2	5.7	0.0	64.9	2968
LAND (X_2)	227.3	323.4	6.5	2398.0	2968
Capital (X_3)	302797.3	339429.7	242.5	3439738.7	2968
Materials (X_4)	65746.8	104290.2	425.9	1016633.8	2968
		Organic			
Output(Y)	183395.8	85088.9	65536.0	308916.0	6
LABOUR (X_1)	2.0	1.0	0.8	3.4	6
LAND (X_2)	147.7	18.0	111.0	155.0	6
DSE441 (X_3)	120640.0	21880.1	93042.9	150403.1	6
DSE275 (X_4)	5706.6	2291.6	4101.6	10282.7	6
		All farms			
Output(Y)	207223.6	339948.9	687.4083	3664902	3000
LABOUR (X_1)	3.400625	6.491146	0.01	76.6558	3000
LAND (X_2)	233.8631	345.1116	6.51	2859.61	3000
DSE441 (X_3)	306723.4	350264.3	242.4732	3439738.7	3000
DSE275 (X_4)	68627.2	120697.9	425.9439	1578782.5	3000

Source: Own calculation based on FADN data

3.8.4 Method

We model production technology with an SFA model. Traditional frontier models assume that all firms face common technology. However, in practice firms use different technologies for a variety of reasons (Tsionas, 2002).

As the main goal of this paper is to compare organic and conventional farms and these group of farms certainly use different technologies we apply a Random Parameter Model (RPM) which allow us to consider technological differences among farms.

The RPM, following Greene (2005), may be written as follows:

$$y_{it} = \alpha_i + \boldsymbol{\beta}_i'\boldsymbol{x}_{it} + \beta_{ti}t + v_{it} - u_{it}, \tag{1}$$

where

$$v_{it} \sim N[0, \sigma_v^2],\ v_{it} \perp u_{it}$$

$$u_{it} = |U_{it}|, U_{it} \sim N[0, \sigma_u],$$

$$\alpha_i = \bar{\alpha} + \alpha_w w_i,$$

$$\boldsymbol{\beta}_{xi} = \overline{\boldsymbol{\beta}}_x + \boldsymbol{\beta}_{xw} w_i,$$

$$\beta_{ti} = \bar{\beta}_t + \beta_{tw} w_i, \text{ where}$$

, i=1,…,N indicating the number of farms; t=1,…,T indicating the time period, w is an unobservable latent random term; $\alpha_i, \boldsymbol{\beta}_{xi}, \beta_{ti}, \alpha_w, \boldsymbol{\beta}_{xw}, \beta_{tw}$ denote the parameters to be estimated, u_{it} represents technical inefficiency, and v_{it} stands for statistical noise (Greene, 2005). y_{it} represents the output variable and $\boldsymbol{x}_{it}$ are inputs.

Furthermore, based on the estimated parameters of the RPM, we constructed multilateral-consistent Törnquist-Theil TFP index (Caves et al., 1982). This productivity index between farm i in period t and the sample average can be formulated as follows:

$$\ln \mathrm{TFP}_{it}^{TTI} = \left(\ln y_{it} - \overline{lny}\right) - \frac{1}{2}\sum_k (S_{kit} + \overline{S_k})\left(\ln x_{kit} - \overline{\ln x_k}\right) \tag{2}$$

, where $k = 1, \dots, K$ inputs; and S stands for share of inputs. A bar above a variable refers to the arithmetic mean of the variable over all sample observations.

Moreover, a simple comparison of the performance indicators between organic and conventional farms might give biased results, because the assignment of farms into the groups is not random, in other words selection bias might affect the results of comparison.

Therefore, the basic objective of an unbiased comparison is to get rid of selection bias. The two most common methods of accounting for selection bias in social sciences are matching and Difference in Difference (D-i-D) methods. In this paper, we use propensity score matching (PSM) in order to account for selection bias (Rosenbaum-Rubin, 1983a; 1983b).

3.8.5 Results

3.8.5.1 Parameter estimates of the Random Parameter Model

Selected parameter estimates of the estimated Translog production SF Model are presented in Table 2. The results show that all of the first order coefficients are statistically significant and have the expected sign (positive), i.e. monotonicity criteria that is suggested by production theory is satisfied. We conducted several tests before choosing this model. First, we tested Translog against Cobb-Douglas functional form using Likelihood ratio test. The test clearly rejected Cobb Douglas functional form.

Next, we compared traditional Normal/Half-Normal SFA model (where the effect of heterogeneity is not accounted for), True random effect Model (where heterogeneity affect only the intercept) with

RPM (where heterogeneity affect not only the intercept, but all of the input variables, i.e. it has an effect on marginal productivity of all of the inputs) based on Akaike Information Criteria (AIC). The test clearly showed that RPM fits better to this data. The statistically significant values of all of the scale parameters also indicate that RPM fits well to these data and it is important to consider the effect of heterogeneity not only on the intercept but on input variables, too. Moreover, results show that land input was the most influential in the production and labour was the least important. Interestingly, the estimate of technological change is negative. One possible explanation for this negative sign is that technological change measured in this way does not measure purely the changes in technology and instead is a combined measure of technical and environmental change; that is, the negative sign might be a consequence of worsening weather condition. However, further research is needed to examine the effect of weather on the production, but this is out of the scope of this paper. Another interesting feature is the nature of technological change. According to these estimates the nature of technological change was land using and intermediate consumption saving.

Table 2: Parameter estimates (selected)

	Coefficients	**Standard Error**	**z**	**Prob |z|>Z***	**95% confidence interval**	
Random parameters						
Constant	0.257***	0.009	29.020	0.000	0.239	0.274
Time	-0.012***	0.002	-5.340	0.000	-0.017	-0.008
Labour	0.073***	0.007	9.830	0.000	0.057	0.086
Land	0.471***	0.013	35.980	0.000	0.445	0.497
Capital	0.109***	0.005	20.040	0.000	0.099	0.120
Materials	0.371***	0.012	32.110	0.000	0.349	0.394
Non-random parameters						
Time*Time	0.007**	0.004	2.010	0.044	0.000	0.015
Time*Labour	-0.001	0.003	-0.270	0.784	-0.007	0.006
Time*Land	0.040***	0.006	6.980	0.000	0.029	0.052
Time*capital	0.001	0.002	0.240	0.808	-0.004	0.005
Time*Materials	-.032***	0.005	-6.200	0.000	-0.042	-0.022
Asymmetry and variance parameter						
Sigma	0.395***	0.004	94.890	0.000	0.387	0.404
Lambda	3.428***	0.182	18.800	0.000	3.071	3.786
Scale parameters for random variables						
Constant	-0.224***	0.004	-53.340	0.000	-0.233	-0.216
Time	0.014***	0.002	6.770	0.000	0.010	0.019
Labour	-0.030***	0.006	-5.460	0.000	-0.041	-0.019
Land	-0.058***	0.010	-5.770	0.000	-0.078	-0.039
Capital	0.011***	0.004	2.610	0.009	0.003	0.020
Materials	0.099***	0.008	12.100	0.000	0.083	0.115

Source: Own calculation based on FADN data

3.8.5.2 Drivers of technical efficiency

In order to examine drivers of technical efficiency we regressed TE on different exogenous drivers: Economic Size Unit (ESU), education (of farm manager), other income, soil quality, number of owners, irrigate, age (of farm manager) and organic. We used the variable irrigate as a dummy variable, it shows whether a farm has some irrigated land or not. Organic is also a dummy variable: 0 conventional farms; 1 organic farms. Results are shown in Table 3.

Table 3: Drivers of technical efficiency

	Coefficients	Standard Error	z	Prob |z|>Z*	95% confidence interval	
Economic Size Unit	0.647D-04***	.201D-04	3.220	0.001	.252D-04	.104D-03
Education	0.002***	.435D-04	36.750	0.000	0.002	0.002
Other Income	0.221***	0.008	28.970	0.000	0.206	0.235
Soil Quality	0.005***	0.000	15.210	0.000	0.005	0.006
Nr. Of owners	-0.001***	0.000	-5.330	0.000	-0.001	-0.001
irrigate	0.074***	0.015	5.060	0.000	0.045	0.103
Age	0.001***	.365D-04	11.120	0.000	0.000	0.000
Organic	0.521D-04	.418D-04	1.250	0.213	-0.298D-04	.134D-03

Source: Own calculation based on FADN data. Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.. ***, **, * ==> Significance at 1%, 5%, 10% level.

Table 3 shows: the higher value of ESU, education, other income, soil quality, irrigation and age increase technical efficiency whereas the higher number of owners decrease. We included also the variable organic to test whether organic production affect technical efficiency or not. The result shows that it does not have any significant effect on TE.

3.8.5.3 Comparison of Indicators

Table 4. contains the comparison of 4 profitability indicators, 4 partial productivity measures and two additional indicators: market orientation and equity ratio. The calculation of these indicators can be found in the Appendix.

Table 4 shows that the profitability of organic farms is higher and the difference is statistically significant for all of the calculated profitability indicators. Land and Material productivity is also significantly higher for organic farms, whereas capital productivity is significantly higher for conventional farms. There were no significant differences for the other indicators.

Table 4: Comparison of indicators between conventional and organic farms

	Conventional	Organic	p-value
profitability 1	1.23	2.73	0.000
profitability 2	1.62	3.50	0.000
profitability 3	0.88	1.92	0.001
profitability 4	1.16	2.46	0.000
labour productivity	83248.63	102477.90	0.154
land productivity	880.12	1211.08	0.073
capital productivity	3.14	1.64	0.011
material productivity	1.63	4.24	0.000
market orientation	0.24	0.24	0.946
equity ratio	0.85	0.92	0.621

Source: Own calculation based on FADN data

3.8.5.4 Comparison of TE and TFP

The mean comparison of estimated TE and TFP scores can be found in Table 5.

Table 5: Mean comparison of TE and TFP

	Mean	Standard Deviation	Minimum	Maximum	Observations	Prob > |z|
			TE			
Conventional farms	1.01	0.13	0.48	1.34	2968	-
Organic farms	0.95	0.15	0.78	1.18	6	-
Mann-Whitney test	-					0.322
			TFP			
Conventional farms	0.76	0.13	0.12	0.96	2968	-
Organic farms	0.72	0.18	0.50	0.96	6	-
Mann-Whitney test	-					0.526

Source: Own calculation based on FADN data

Table 5 shows that both the TE and TFP of conventional farms are to some extent higher compared to organic farms. We tested whether these differences are statistically significant or not using Mann-Whitney test. The test shows that the differences are not significant. However, this comparison may be biased, therefore in the next section we apply matching method in order to correct for sample selection bias.

3.8.5.5 Comparison of TE and TFP using matching method

The decision of how many variables to include into the matching procedure is widely discussed in the literature. In order to choose the applied variables, we checked differences between organic and conventional farms in terms of standardised bias. We found that there is a difference in economic size, educational level and soil quality between these groups of farms. Therefore, in our matching procedure we control for these variables. Educational level was measured in a scale from 1 to 5: 1 lowest educational level, 5 the highest educational level. Soil quality is based on a Hungarian soil qualification system; the higher value means better quality.

We tested different matching algorithms and we choose the one where the mean bias was the smallest after matching. Figure 1 shows the mean bias matching for different matching algorithms and for different number of nearest neighbours. It shows that the mean bias is the lowest with 6 nearest-neighbour, therefore we choose this type of matching for the comparison of farms' performance.

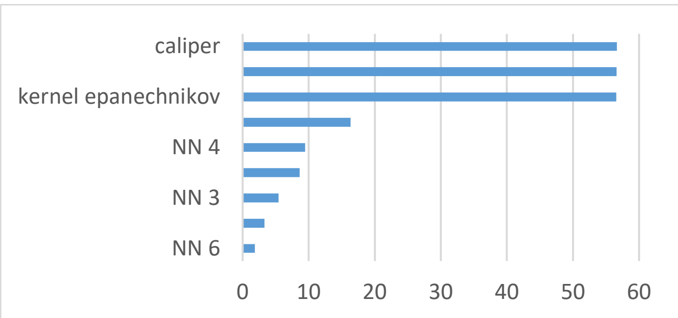

Figure 1: Mean bias after matching. Source: Own calculation based on FADN data

Table 6 shows that the applied matching algorithm, balanced well the sample; all the differences in the covariates that were statistically significant before matching disappeared after matching.

Table 6: Differences in the matched and unmatched sample

Variable	Unmatched(U)/ Matched(M)	Mean Treated	Mean Control	%bias	% reduce bias
ESU	U	73.5	141.7	-46.9	
	M	73.5	72.6	0.6	98.7
Soil quality	U	16.9	18.0	-12.7	
	M	16.9	17.3	-4.9	61.1
Education	U	1.0	2.1	-110.3	
	M	1.0	1.0	0.0	100.0

Source: Own calculation based on FADN data

The results of treatment effect analysis are reported in Table 7.

Table 7: Average Treatment effect on the Treated

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf. Interval]	
TE	-0.045	0.078	-0.580	0.564	-0.199	0.108
TFP	-0.061	0.075	-0.810	0.416	-0.209	0.086

Source: Own calculation based on FADN data

Results show that the differences between organic and conventional farms in TE and TFP is not statistically significant.

3.8.6 Conclusions and Limitations

The aim of this paper was to compare the TE and TFP of organic and conventional COP crop producing farms. We estimated TE using a random parameter stochastic production frontier. The model suited well to this dataset, most variables were significant and criteria suggested by economic theories were fulfilled. Based on the estimated parameters of the model we constructed a Törnquist-Theil TFP index. First, we compared the performance of the groups with standard statistical test. Results showed that both the TE and TFP of organic farms are smaller, but the difference was not statistically significant. Second, we compared TE and TFP based on propensity score matching in order to eliminate potential selection bias. After controlling for selection bias the difference remained insignificant. In addition, we compared several indicators concerning farms technical and economic performance. Results showed that profitability, land and material productivity are significantly higher for organic farms. However, because of the low number of organic farms in our sample, all results should be interpreted with caution.

One limitation of such kind of comparison is the lack of appropriate deflators. In order to estimate a production frontier using FADN data in most of the cases, one has to use implicit quantity indices for the output variable(s) and some of the input variable(s) (e.g. intermediate consumption). Organic farms usually can sell their products for higher prices and might buy some of their inputs for higher prices compared to conventional farms. In case the same price indices are used to deflate the monetary variable(s) used in the production frontiers both for organic and conventional farms., the implicit quantities will be biased in the case of organic farms. With more appropriate price indices, more accurate performance analysis would be possible.

Our results have also implications for policy. First, they show that the construction of different price indices for organic and conventional farms is an important first step to make more reliable evaluation concerning the differences in production efficiency between the different production systems. Second, the low number of organic farms suggest, if increasing the number of organic farms or the share of organic food production is a policy goal, more targeted measures are needed to attract farmers to convert their farms to organic.

3.8.7 References

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3.8.8 Appendix

Definitions of indicators of technical-economic farm performance

#	Group	Name	Description	Definition in FADN
1	Profitability indicators	Private revenue-cost-ratio not considering remuneration of owned production factors	Revenue / (intermediate expenses+ depreciation + paid interest + paid labour + paid rent): Expresses ability of a farm to cover costs, not having to cover costs for owned production factors, with its private revenues	SE131 / (SE275 + SE360 + SE370 + SE375 + SE380)
2	Profitability indicators	Public revenue-cost-ratio not considering remuneration of owned production factors	(Revenue + subsidies) / (intermediate expenses + depreciation + paid interest + paid labour + paid rent) Expresses ability of a farm to cover costs, not having to cover costs for owned production factors, with its private revenues and public subsidies	(SE131 + SE605) / (SE275 + SE360 + SE370 + SE375 + SE380)
3	Profitability indicators	Private revenue-cost-ratio considering remuneration of owned production factors	Revenue / (intermediate expenses + depreciation + imputed interest + imputed labour + imputed rent Expresses ability of a farm to cover all costs, including those for owned production factors with its private revenue	SE131 / (SE275 + SE360 + (SE436 * imputed interest rate) + (SE010 * hours of fulltime AWU * imputed wage per hour) + (SE025 * imputed rent per ha)).
4	Profitability indicators	Public revenue-cost-ratio considering remuneration of owned production factors	Revenue + Subsidies / (intermediate expenses + depreciation + imputed interest + imputed labour + imputed rent Expresses ability of a farm to cover all costs, including those for owned production factors with its private revenue and public subsidies	(SE131+Se605) / (SE275 + SE360 + (SE436 * imputed interest rate) + (SE010 * hours of fulltime AWU * imputed wage per hour) + (SE025 * imputed rent per ha)).

5	Partial productivity indicators	Average product of land	Partial productivity indicator, describing output per unit of the input land	Output / land
6	Partial productivity indicators	Average product of labour	Partial productivity indicator, describing output per unit of the input labour	Output / labour
7	Partial productivity indicators	Average product of capital	Partial productivity indicator, describing output per unit of the input capital	Output / capital
8	Partial productivity indicators	Average product of intermediate expenses	Partial productivity indicator, describing output per unit of the input intermediate expenses	Output / intermediate expenses
9	Additional indicators	Market orientation	Revenue / (Revenue + subsidies) Describes how much a farm relies on public subsidies, compared to private revenues	SE605 / (SE131 + SE605)
10	Additional indicators	Equity ratio	Equity / total assets	SE501 / SE436

Source: Based on suggestions of BOKU

For imputed labour we used the ratio of paid wages (SE370) to paid labour input (SE020), devided by 1800(hours/year of AWU in Hungary). For imputed interest rate, we used the base rate of the Central Bank of Hungary. For imputed land rent prices we used the land rent prices of arable land from the Hungarian Statistical Office (HCSO). For every imputed value we used the average values of the examined time period (2010-2015).

3.9 Farm technical and economic performance depending on the degree of ecological approaches: The case of olive farms in Crete, Greece (DEMETER)

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3.9.1 Introduction

Olive cultivation is a well-established agricultural activity in the Mediterranean region and Greece. The activity is traditional in many parts of the country where a total of 792,642 ha is cultivated, with the Prefectures of Peloponnese and Crete accounting for 27% and 23% of the total area of olive groves kept in the country, respectively (HAS[14],2017). The total number of trees cultivated in Greece in 2017 was 148,053,557, which corresponds to an average density of 187 trees per hectare.

Olive orchards are mainly cultivated in Greece for the purpose of olive oil production, which reached a total of 311,727 tons in 2017. The production of olive oil has received extra attention due to its significant role in the Mediterranean diet, recently acknowledged by UNESCO as an Intangible Cultural Heritage of Humanity (UNESCO, 2013). Indeed, the benefits of olive oil are well known globally (Covas et al., 2006), and the demand for the product is estimated to increase further, with new producing countries also appearing in the future (Mili and Bouhaddane, 2021).

On the production side, these developments increase the interest of agriculturalists in the activity and the factors determining its economic performance and competitiveness in the global market. Our analysis focuses on the economic performance of Greek olive farms and examines productivity, profitability, and efficiency indicators and drivers at the farm level. The analysis focuses on the region of Crete and, in particular, the Prefectures of Heraklion and Lasithi, located in the eastern part of the island. A total of 89,644 ha is cultivated in Heraklion with olive groves, and 27,086 ha of olive groves are located in Lasithi (HAS, 2017). These correspond to 15% of the total olive trees of the country and 17% of the total olive production. One of the reasons why the activity is common in Crete is the existing climatic conditions. Olive trees are characterised by an increased tolerance to drought and salinity (see, for example, Vasilaki et al., 2008), and they are well adapted to the Mediterranean climate of the Island.

The average yield of olive groves in the area under investigation reaches 0.5 tons/ha, which exceeds the national average by approximately 12%. The density of the olive groves is slightly below the national average, which implies that the increased yield is the result of the higher productivity of the Cretan olive groves. The number of olive farms located in the area under investigation was 52,707 in 2016, accounting for 12% of the total Greek olive farms (HAS, 2016).

Organic olive cultivation is quite common in Greece. In the study area, 3% of the total area covered with olive groves is certified as organic, which corresponds to 3,721 ha and 1,016 farms (Tzouramani et al., 2019). Another common quality certification in the area under investigation is AGRO 2, which refers to the Integrated Management System (Duvaleix et al., 2020). The number of farms that held an AGRO 2 certification in the area under study was 2,508 in Heraklion and 2,658 in Lasithi, which equals an area of 6,623 ha and 5,422 ha, respectively (Duvaleix et al., 2020).

[14] Hellenic Statistical Authority

The economic performance of the olive farms in this case study is estimated in our analysis using a number of productivity and profitability indicators described in the sections *Data* and *Methods*. Additionally, the technical efficiency of the olive farms is estimated using Data Envelopment Analysis (DEA). Efficiency analysis is commonly implemented in agricultural economics (Lansink and Reinhard, 2004; Theodoridis et al., 2006; Zhu and Demeter, 2012; Latruffe et al., 2017; Madau et al., 2017; Kurdyś-Kujawska et al., 2021). The technical efficiency of olive farms has also been investigated in a number of studies abroad and in Greece (Lachaal et al., 2005; Lambarraa et al., 2007; Kashiwagi et al., 2012; Beltrán-Esteve, 2013; Jurado et al., 2017; Niavis et al., 2018; Stilitano et al., 2019; Raimondo et al., 2021).

The majority of these studies also investigate the endogenous and exogenous variables that determine the technical efficiency of the farms using various socioeconomic and technical variables (second stage analysis) (see, for example, Jurado et al., 2017; Niavis et al., 2018) like education level, age, experience, subsidies received, etc.

The same path was also followed in this case study, in which a second stage regression analysis is performed to explore further the determinants of technical efficiency of olive farms. Additionally, the productivity, profitability, and efficiency indicators of the olive farms are examined across different agroecological farm types identified within the LIFT project to explore the effect of the degree of ecological approaches on the economic performance of the farms.

3.9.2 Data

The economic analysis of the Cretan farms is implemented using the data gathered during the LIFT large scale farmer survey. The data were collected from olive and vineyard farms for which relevant economic indicators were estimated as described in the *Methods* section. The analysis then focuses on specialised olive farms for which technical efficiency was calculated.

In our case study, we consider a farm as specialist olive when two-thirds of the farm output (revenues) come from olives (mainly oil production)[15]. Following this rule, 73 out of the 108 farms of the Greek sample are characterised as specialist olives. This group of farms was then checked for outliers since the DEA methodology that was performed is sensitive to outliers. Eight farms were excluded from the final sample of olive farms either for reporting no revenues or reporting zero intermediary, capital, or labour costs (incomplete interviews). The remaining 65 farms that were considered in the analysis have an average size of 4.9 hectares which yields on average 13,340€ of output (excluding subsidies) and correspond to 2,175 hours of labour (1.24 FTE[16]) (see also Table 3).

The specialist olive farms were almost equally distributed between the two case study areas since 32 are located in Heraklion and 33 in Lasithi. Their land is located in low altitudes, less than 600m, while 30 of the farms report their farmland to be located at an altitude less than 300m. The majority of land is also irrigated (57 farms).

Regarding their ecological profile, 27 farms are organic, 44 fall into the conservation farms category, 5 are considered low input, 5 are integrated, and 5 are characterised as medium input, according to the

[15] This rule is in line with the typology of farms in FADN according to their Standard Gross Margin (SGM). In our analysis we use the value of output instead of the SGM since the specific costs considered in the latter cannot be broken down to the activities of the farms (https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:31985D0377&from=EN). The use of revenues for the definition of specialist olive farms in our analysis (compared to the use of GSM), implies that we consider the costs used for the SGM estimation to be proportional to the revenues when broken down between activities.

[16] One Full Time Equivalent (FTE) is equal to 1,750 hours of labour.

LIFT survey-based protocol for farm typology, developed within the LIFT project (Rega et al., 2021). The farm owners are in their majority male (52), and their average age is 53 years. They are considered experienced farmers since their average years of experience in agriculture are 31. Twenty-seven of them have higher education, and 33 have finished either middle school or high school. It should also be mentioned that 14 of them have agricultural education provided either at high school or at the university level. The labour inputs mainly derive from the farm household since 75% of the total labour comes from the family members. On average 1.1 members of the family offer their employment in the olive farms, while farms also occupy 2.89 hired workers, mainly seasonal, who perform tasks like harvesting olives or pruning the olive trees.

Regarding the managerial profile of the olive farms, it should be emphasised that even though they specialise in olive production, pluriactivity is common since, on average, only one-third of the household income comes from agriculture. Finally, for the olive farms of the sample, the main distribution channel is the producers' organisations, followed by merchants and wholesalers, and processors. At the same time, a very small part of the production is directly sold to consumers at an average selling price of 3.18€/kilo.

The summary statistics of the main cost elements of the olive farms are presented in Table 1. As can be seen in Table 1, labour is an important part of the annual costs of the activity. Energy costs, which refer mainly to fuel costs, are also exceptionally high mainly because of Greek farms' structure, which usually consists of many land plots, often located at a distance from one another. This requires frequent road trips to carry out the necessary tasks. Finally, it should be noted that, the cost elements presented in Table 1 are characterised by high standard deviation, which reflects the heterogeneity of the olive farms that are included in the sample, in terms of size and level of intensification. Additional economic and profitability indicators of the farms are provided in the *Results* section.

Table 1: Main average annual costs of olive farms (€).

	Mean Value	St. Deviation	CV
Intermediary expenses			
Contract labour	753	2,661	353.39%
Energy costs	1,810	2,272	125.52%
Inorganic fertilisers	509	893	175.44%
Manure	637	2,397	376.30%
Pesticides	487	916	188.09%
Water	708	1,204	170.06%
Labour costs			
Family labour	6,616	5,499	83.12%
Hired labour	2,510	5,764	229.64%
Fixed costs			
Depreciation	3,621	2,703	74.65%
Interests	945	1,064	112.59%
Rents	2,205	1,745	79.14%

3.9.3 Methods

The first step of our analysis refers to the estimation of certain productivity and profitability indicators for the olive farms[17]. Table 2 contains the definitions of the indicators used, which were calculated using the cost data (the main elements are already presented in Table 1) and the revenues of the farms. It should be emphasised that even if the case study refers to specialist olive farms, other agricultural activities may be present in the farms, which offer one-third of the revenues or less, and therefore all costs and revenues refer to the whole farm and not only to the olive groves.

In order to test for statistically significant differences in the profitability and productivity indicators of farms along their degree of ecological approaches, the Mann-Whitney test was performed. This test was chosen as it does not assume a normal distribution of the population.

Table 2: Definition of productivity and profitability indicators

Indicator	Definition
Private revenue-cost-ratio not considering remuneration of owned production factors	Revenue / (intermediate expenses+ depreciation + paid interest + paid labour + paid rent)
Public revenue-cost-ratio not considering remuneration of owned production factors	(Revenue + subsidies) / (intermediate expenses + depreciation + paid interest + paid labour + paid rent)
Private revenue-cost-ratio considering remuneration of owned production factors	Revenue / (intermediate expenses + depreciation + paid interest + paid labour + paid rent + imputed interest + imputed labour + imputed rent)
Public revenue-cost-ratio considering remuneration of owned production factors	(Revenue + subsidies) / (intermediate expenses + depreciation + paid interest + paid labour + paid rent + imputed interest + imputed labour + imputed rent)
Average product of land	Partial productivity indicator, describing output per unit of the input land
Average product of labour	Partial productivity indicator, describing output per unit of the input labour
Average product of capital	Partial productivity indicator, describing output per unit of the input capital
Average product of intermediary expenses	Partial productivity indicator, describing output per unit of the input intermediary expenses
Market orientation	Revenue / (Revenue + subsidies)
Equity ratio	Equity/total assets (not applicable in the case of olive farms have no loans)

The next step of the economic analysis of the olive farms refers to the estimation of their technical efficiency. The analysis involves the construction of a model that can depict the production process of the olive farms. All farms in the sample use a mix of inputs (capital, labour, and land) to produce an output. Some of these farms use their inputs more efficiently than others to produce the same output with less input or use the same input to produce more output. The analysis performed estimates an

[17] The partial productivity and profitability indicators have been estimated for all the Greek farms (108 in total) that are included in the LIFT large scale farm survey as part of this deliverable. The results are provided in an attached excel file.

efficiency score for each farm in the sample, indicating how much the farm can reduce its inputs and still produce the same amount of output (input-oriented analysis). Table 3 summarises the statistics of the input and output variables that were used in the model. As in the case of the cost elements presented in Table 1, the standard deviation of the input and output variables is high, indicating the heterogeneity of the olive farms included in the sample.

Table 3: Definitions and descriptive statistics of the input and output variables used in the analysis.

	Definition	Mean Value	St. Deviation
Inputs			
Intermediary expenses	All intermediary costs (e.g. fertilisers, pesticides, energy costs, contract labour)	5,242.45	5,970.07
Capital	Value of assets minus land	12,437.13	13,998.50
Labour	Labour inputs in hours	2,175.34	2,368.80
Land	Land in Ha	4.91	3.67
Output			
Revenue	Total value of farm output (excluding subsidies)	13,340	24,310.57

The technical efficiency of the olive farms is estimated using an input-oriented, data envelopment analysis (DEA) model. DEA is a non-parametric method to estimate efficiency, developed by Charnes et al. (1978). The methodology is based on the construction of a production frontier where all the decision-making units (DMU), or in our case farms, that use a minimum level of inputs to produce a certain output lie. This production frontier is deterministic, and every deviation from the frontier is considered as inefficiency. The main advantage of DEA is that, unlike other methodologies (e.g., stochastic frontier analysis), it does not a priori assume a specific form of a production function. In our analysis we use a variable returns to scale (VRS) specification to overcome the issue of scale inefficiencies (see for example Coelli et al., 2005; Ji and Lee, 2010), and the following model is formulated:

$$\begin{gathered} \min \theta, \\ \text{Subject to:} \\ -yi + Y\lambda \geq 0 \\ \theta xi - X\lambda \geq 0 \\ NI'\lambda = 1 \\ \lambda \geq 0 \end{gathered} \tag{1}$$

where: θ is the DMU's index of technical efficiency, yi, and xi, refer to the outputs and inputs of DMU i, respectively, Yλ and Xλ are the projections on the constructed frontier and **NI** is a $n \times 1$ vector of ones, that is used to prevent the comparison of farms with unequal sizes. This way Scale Efficiency (SE) can be calculated as the ratio of the constant returns to scale (CRS) TE score to the VRS TE score. The DMU is technically efficient when θi = 1. Therefore, 1 − θ indicates how much the DMU can proportionally reduce its inputs and still produce the level of output.

The final step of our analysis involves the second-stage regression analysis that is performed to investigate the association of the efficiency scores that the DEA model provides with certain characteristics of the farm and farmer. The truncated regression analysis was performed using the set of explanatory variables presented in Table 4.

The truncated regression analysis was chosen over the Ordinary Least Squares (OLS) regression since the estimations performed by the OLS regression analysis are considered biased and inconsistent, because the dependent variable, which consists of the efficiency scores is censored (Samut et al., 2016). Therefore, it is better to have the estimations done by Tobit or truncated regression; however, truncated regression models are generally preferred and considered more appropriate (Simar and Wilson, 2007; Dai et al., 2016; Li et al., 2017).

Table 4: Definition of variables used in the second-stage regression analysis.

Variable	Definition
Dependence on subsidies	Subsidies to total revenues ratio
Low-input farms	Binary variable that takes the value 1 if the farm is characterised as Low-input according to the LIFT typology and 0 if the farm is not characterised as low input
Organic	Binary variable that takes the value 1 if the farm is characterised as organic according to the LIFT typology and 0 if the farm is not characterised as organic
Experience	Number of years of experience in farming
Inorganic fertilisers	Cost of inorganic fertilisers (€)
Water	Cost of irrigation water (€)
Agricultural education	Binary variable that takes the value 1 if the farmer has agricultural education and 0 otherwise

The variables used in the truncated regression analysis involve demographic characteristics of the farmer (experience and education) and managerial characteristics of the farm (market orientation, inorganic fertilisers expenses, and water expenses). Additionally, the degree of ecological approaches was also used in the explanatory variables set (organic and low input farms). Other variables were considered but not used in the regression analysis for various reasons. Age of the farmer was strongly correlated with the experience variable and therefore was removed from the regression analysis. Furthermore, the inclusion of site-specific variables (location of farms and altitude) in the regression analysis did not offer additional explanatory power to the variability of the dependent variable (efficiency scores). Managerial characteristics like farmer's objectives, off-farm income, distribution channel, family to total labour ratio etc.) were also excluded from the regression model for the same reason. The statistical analysis as well as the DEA analysis were performed in STATA/SE 13.0.

3.9.4 Results

Table 5 presents the summary statistics of the partial productivity and profitability indicators for the olive farms. The profitability indicators reveal that the olive farms in our case study can cover their intermediary expenses, the depreciation costs, and their paid labour and rents, since both the private and public revenue-cost ratios are higher than one, when the remuneration of owned production factors is not considered. However, the farms cannot cover the remuneration of their owned production factors since the corresponding public and private revenue-cost ratio are lower than one. These results indicate that though olive farms can continue to operate in the short-run, adjustments need to be made so that net profit can be achieved. It should be emphasised also, that the years 2016-2018, were characterised by low yields in olive farms mainly due to unfavourable weather conditions and olive fly problems.

As far as the partial productivity indicators are concerned, it is important to emphasise that the productivity of land is quite high (significantly higher than the rent per hectare) and also the productivity of labour is higher than the average wage per hour, as estimated by the gathered data (4.41€/ hour).

The profitability and partial productivity indicators were also examined across the degree of ecological approaches, using the LIFT survey based protocol for the olive farm typology. The summary statistics of the partial productivity and profitability indicators per farm type are also presented in Table 5. As can be seen by the results the average partial productivity and profitability indicators are smaller in the case of medium- input farms, followed by conservation farms. The highest scores of the productivity and profitability indicators are presented in the agroecological farm type followed by the low-input/integrated farms. Organic farms also achieve better profitability and partial productivity scores than medium input and conservation farms.

The Mann Whitney test was performed to examine the statistical significance of the above differences in the profitability and partial productivity indicators across the degree of ecological approaches. Agroecological farms had statistically significant higher labour and land productivities as well as private and public profitability indicators considering remuneration of owned inputs (z=-2.975***[18], z=-1.611*, z=-1.952**, and z=-1.897**, respectively). Integrated and low input farms have a statistically significant different public and private revenue-cost ratio and land and labour productivities (z=-2.031**, z=-2.155*, z=-1.797** and z=-3.324***, respectively). Finally, organic farms appear to have statistically significantly different public and private revenue-cost ratio considering remuneration of owned inputs than non-organic farms and also different labour productivity (z=-2.117**, z=-1.884*, z=-2.157**, respectively).

The average technical efficiency of olive farms was estimated equal to 0.68. This result indicates the maximum feasible equi proportionate reduction of inputs that can be achieved, given the level of output. Specifically, the average TE score indicates that all inputs can be reduced by 32% without compromising the output level of the farms. This finding is in accordance with other studies that use similar analysis and focus on the estimation of the technical efficiency of olive farms in the Mediterranean region (Lachaal et al., 2005; Lambarraa et al., 2007; Kashiwagi et al., 2012; Stilitano et al., 2019; Raimondo et al., 2021). However, lower scores of technical efficiency are also commonly found in the case of Mediterranean olive farms (Beltrán-Esteve, 2013; Jurado et al., 2017). Tzouvelekas et al. (2001) estimated the technical efficiency of Greek conventional olive groves at 0.54, indicating that there is a lot of room for improvement regarding the utilisation of inputs. On the other hand, Niavis et al. (2018) estimated the technical efficiency of extensive olive farms in the area of Pelion, Greece, to be much higher (0.86).

[18] Asterisks are used to summarise statistical significance level as: * corresponds to P ≤ 0.01, ** corresponds to P ≤ 0.05, *** corresponds to P ≤ 0.001

Table 5: Summary statistics of the profitability and productivity indicators for the sample farms and per agroecological type

	Total farms	Medium input	Conservation	Organic	Integrated/ Low input	Agroecological
Indicator	**Mean (Standard deviation)**					
Market orientation	0.73(0.27)	0.58(0.21)	0.70(0.24)	0.73(0.25)	0.86(0.11)	0.83(0.12)
Average product of intermediary expenses	3.37(6.26)	1.40(1.07)	2.37(1.76)	2.68(2.06)	2.80(1.86)	2.93(2.12)
Average product of capital	1.79(2.23)	1.48(1.80)	1.91(2.14)	1.99(2.34)	2.19(1.56)	2.43(1.69)
Average product of labour	5.83(4.58)	3.44(3.52)	5.82(4.59)	7.74(5.64)	14.36(5.23)	14.95(5.84)
Average product of land	2390(1854)	2065(2166)	2197(1902)	2976(2270)	3678(1630)	3724(1878)
Private revenue-cost ratio not considering remuneration of owned production factors	1.01(0.70)	0.77(0.60)	0.89(0.53)	1.08(0.76)	1.13(0.44)	1.17(0.50)
Public revenue-cost ratio not considering remuneration of owned production factors	1.30(0.73)	1.19(0.74)	1.22(0.57)	1.38(0.79)	1.33(0.52)	1.42(0.56)
Private revenue-cost ratio considering remuneration of owned production factors	0.51(0.33)	0.36(0.33)	0.49(0.31)	0.62(0.41)	0.78(1.22)	0.80(2.45)
Public revenue-cost ratio considering remuneration of owned production factors	0.66(0.36)	0.56(0.43)	0.67(0.34)	0.79(0.42)	0.92(0.27)	0.97(0.29)

*The number of sample farms is 65, the number of medium input farms is 5, the conservation farms are 44, the Integrated/Low input farms are 5, the Organic farms are 27 anf 4 farms are Agroecological.

The results for scale efficiency (SE) indicate that the size of the majority of the olive farms is not optimal, meaning that their level of production should be adjusted. Specifically, 49 farms operate at increasing returns to scale (IRS), which means that their size (production level) should be increased. On the other hand, 7 farms operate at decreasing returns to scale (DRS), which means that their optimal size should be smaller. Finally, 9 farms operated under constant returns to scale (CRS), or in other words, have the optimal farm size.

The reasons for technical inefficiency were further examined using truncated regression analysis, as mentioned in the sections *Data* and *Methods*. The results are presented in Table 7. The dependency on subsidies has a strong negative and statistically significant effect on the TE score (based on the coefficient and the p-value of this variable). This finding indicates that subsidies have a negative effect on the efficiency of farms and is according to the findings of other studies that focus on the technical efficiency of olive farms in Greece and the Mediterranean region (Zhu et al., 2011; Lambarraa and Kallas, 2010).

Table 6: Descriptive statistics of technical efficiency (TE), scale efficiency (SE) and scale of operation.

Sample farms						Medium input	Con-serva-tion	Organic	Conservation /Low input	Agroeco-logical
Variable	**Mean**	**Standard Deviation**	**CV**	**Min**	**Max**	**Mean (standard deviation)**				
TE	0.68	0.28	41%	0.1	1	0.43 (0.32)	0.65 (0.28)	0.82 (0.26)	0.93 (0.10)	0.94 (0.11)
SE	0.78	0.24	31%	0.2	1	0.75 (0.31)	0.76 (0.25)	0.70 (0.27)	0.94 (0.08)	0.97 (0.04)
Scale of operation			Decision making units (DMUs)/farms							
Increasing returns to scale (IRS)			49 (75%)							
Constant returns to scale (CRS)			9 (14%)							
Decreasing returns to scale (DRS)			7 (11%)							

Furthermore, the variable that refers to low input farms has a positive effect on technical efficiency, while the variable that refers to organic farming has no statistically significant effect on technical efficiency. This is an important finding that stresses the significance of the agroecological practices implemented in low-input farms regarding the limited use of inputs like inorganic fertilisers and soil conditioners. On the other hand, the results regarding organic farming seem to be different from the results of similar studies that indicate that organic farms have a higher technical efficiency than conventional olive farms (Artukoglu et al., 2010; Raimondo et al., 2021). However, it should be emphasised that the low input olive farms in our sample are also organic farms which can, to some extent, justify this finding.

Experience also has a positive and statistically significant effect on the technical efficiency of olive farms, much stronger than the effect of agricultural education. These results emphasise the importance of practice when it comes to agricultural activities that can overcome the importance of academic education.

Finally, what is also important to emphasise is the negative effect of the cost of inorganic fertilisers on the technical efficiency of olive farms. This is an indication of how the excessive use of these inputs can be an important determinant of technical inefficiency in olive farms and stress the need to limit their use.

Table 7: Results of the Truncated Regression analysis.

Variables	Coefficient	Std. Err.	z	P>z	[95% Conf. Interval]	
Dependency on subsidies	-1.55	0.5246408	-2.95	0.003	-2.578277	-0.52172
Low-input farms	0.8623388	0.5231186	1.65	0.099	-0.1629548	1.887632
Organic	-0.0540593	0.1294318	-0.42	0.676	-0.3077409	0.199622
Experience	0.009534	0.0056331	1.69	0.091	-0.0015066	0.020575
Inorganic fertilisers	-0.0001289	0.0000696	-1.85	0.064	-0.0002653	7.60E-06
Water	-0.0000739	0.0000498	-1.48	0.138	-0.0001716	2.38E-05
Agricultural education	0.2720899	0.1819541	1.5	0.135	-0.0845336	0.628713
Constant	1.031032	0.2343588	4.4		0.5716977	1.490367

3.9.5 Discussion and conclusions

The efficient use of inputs and the ability of the farms to maintain their level of output while at the same time saving on the amount of resources used, is one of the main challenges of agriculture today, especially in light of the growing demand for food and the input restrictions imposed by the on-going climate change. Main agricultural production resources like land and water are becoming scarce, while at the same time, the pressure for improving farm productivity is increasing to feed the global population. However, it has become apparent that traditional production models are not necessarily characterised by efficiency in input use. At the same time, consumer demands for high-quality and environmentally friendly products is increasing, drawing attention to the study of alternative agroecological practices and their impact on farm economic performance.

In other words, the efficient use of inputs and natural resources is important not only for the farmer - as it improves the economic performance of the farm - but also for policymakers and consumers as it can limit the environmental burdens of agricultural production, release scarce resources and provide goods at lower costs.

This study focuses on estimating the economic performance of Cretan olive farms in terms of productivity, profitability, and technical efficiency indicators. The analysis also considers the degree of ecological approaches of the farms under investigation to determine the extent to which it affects farm economic performance.

The results of the analysis indicate that, even though during the reference period the output of the farms was negatively affected by the environmental conditions and the olive fly damages to production, the operating farms were able to cover their intermediary expenses, their paid rents and labour as well as depreciation costs of their assets. This allowed them to continue their operation in the short run, but the negative profitability indicators when imputed costs are included in the analysis impose a risk for the activity in the long run. Although low yields are significantly affecting the economic output of the farms, additional changes need to be made regarding the level of input use of the farms.

Technical efficiency scores of the olive farms indicate that there is significant room for improvement of their management, as they can reduce their inputs by 32% and maintain the same level of output. The results of the truncated regression analysis indicate that inefficiencies are significantly associated with high dependency on subsidies. At the same time, subsidies help maintain a positive profit, especially during low-yield years, which can be very important for olive production. These results need to be carefully considered by policymakers since one main objective of subsidies, i.e., maintaining farm income, is met. Still, at the same time, another objective, i.e., improving farm structure and management, seems to be lacking. Perhaps the mixture of subsidies provided to the farmer needs to be adjusted to encourage managerial restructuring and technical and economic efficiency.

The analysis also highlighted that agricultural education does not ensure the efficient use of inputs. On the other hand, experience seems to have a positive effect on the ability of farms to increase their technical efficiency. This is particularly important for traditional and well established farming activities like olive cultivation and should be considered when planning extension services. Newcomers in agriculture require sufficient practical training as opposed to theoretical education to compensate for the lack of experience, and extension services should adjust to these needs.

Finally, the results of the analysis indicate that profitability and productivity indicators differ across the various degrees of ecological approaches. Farms characterised as agroecological, low input/integrated, and organic appear to have higher profitability and productivity indicators, while medium-input farms and conservation farms score lower in productivity and profitability. The results of the truncated regression analysis verify the above findings for the case of low-input farms and emphasise that the transition to agroecological practices can improve farm efficiency.

To conclude it should be mentioned that several other factors that appeared to have no statistically significant impact on the technical efficiency scores in this analysis, should be further investigated in the future. The effect of the personal objectives of the farmer on the farm's technical efficiency is not yet clear. At the same time, variables concerning the characteristics of the area e.g., altitude, also had no significant effect on the efficiency scores. However, additional sample farms maybe required to verify this result since the farms in the sample are mainly located in the lowland area.

The analysis can also be performed using the Greek FADN data on olive farms to compare the average efficiency of olive farms. The use of FADN panel data could also address the low-yield problems encountered during the LIFT large-scale survey already mentioned and provide more robust results.

3.9.6 References

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3.10 Dynamics of productivity and efficiency performance in Poland's dairy farms: comparative analysis by different degrees of ecological approaches (IRWiR PAN)

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3.10.1 Introduction and description of the case study

Polish dairy sector is the 4th largest producer of raw milk among all EU-27 member states (after Germany, France and the Netherlands - Eurostat 2021), holding this position since the country's accession to the EU in 2004. The average annual growth rate of the output (raw milk delivered to the dairies) within 2005-2019 equals 2.4%, which consistently led to delivery of 10.9 million tonnes of milk in 2015 and 12.2 million tonnes in 2019. The total production of milk is even higher reaching 14.1 million tonnes in 2019 (GUS 2020).

The number of dairy cows shows a permanent decline trend, reaching 2.28 million heads in 2015 and 2.22 million heads in 2019 (compared to 2.8 million heads in 2004). Yet this decline is compensated by intensification of production processes and increasing productivity. Thus, the annual average production of milk per cow has grown from 4,082 litres in 2004 (GUS 2007) to the 5,803 litres in 2019 (GUS 2020).

The total number of dairy cows in ecological farms across Poland in 2018 equalled 10983 (IJHARS 2019), decreasing by 3.5% compared to previous year. This is merely 0.5% of the total country's population of dairy cows. Yet according to stakeholders (Kolasińska 2019) only about half of the ecological dairy farms sells their milk labelled as such, while the rest sell it as conventional product.

Milk output in ecological farms has declined from 376304 hectolitres in 2010 (IJHARS 2011) to 253081 hectolitres in 2018 (IJHARS 2019). Regional distribution of ecological dairy farms is completely different to overall distribution of ecological farms. Leading positions in this case have the Małopolskie, Podkarpacie and Zachodniopomorskie regions.

In regard to the in-depth analysis carried out, within the Polish FADN database in 2015 there were 2,694 dairy farms, yet only 57 had an ecological certificate and 1 was in the process of conversion. In 2006 this distribution was different: 2,188 dairy farms, within which 25 with a certificate and none in the conversion.

3.10.2 Method

We applied three-step method in order to assess the efficiency of dairy farms in Poland according to their degree of ecological approaches. They are presented in the following three subsections, while the fourth subsection presents the approach to assessment of their potential drivers.

3.10.2.1 Identification of farm types by degree of ecological approaches

In the first step, we applied the LIFT FADN protocol, the final version developed by Rega et al. (2021), in order to distinguish the meaningful groups of dairy farms according to their degree of ecological approaches. We distinguished 8 ecological types - 4 basic: standard (ST), low-input (LI), integrated

(INT), organic (ORG) and 4 mixed types (INT-ORG, LI-INT, LI-INT-ORG, LI-ORG) - see Figure 1 and Table 1.

Analyses were started with 8 types of farms. Their shares in the total sample of dairy farms were over the years 2006-2015 on average as follows: standard (59.1%), integrated (30.2%), low-input (1.1%), organic (0.2%) and for the mixed types low-input integrated (6.9%), integrated-organic (1.5%), low-input integrated organic (1%) and low-input organic (0.1%). We observed over that time an increasing number of farms and an increasing share in the structure for: standard farms (from 881 to 1,844 farms or 40.3% to 68.4%), integrated-organic (from 23 to 44 farms or 1.1% to 1.6%) and organic (from 1 to 9 farms or 0.001% to 0.2%). The opposite was observed in case of: integrated farms (decline from 841 to 684 farms or 38.4% to 25.4%), low-input (from 68 to 16 or 3.1% to 0.6%), low-input integrated (from 348 to 82 farms or 15.9% to 3.0%), low-input integrated organic (from 26 farms to 14 or 1.2% to 0.5%). Only in case of low-input organic farms almost no changes were observed over that time, both in number and structure.

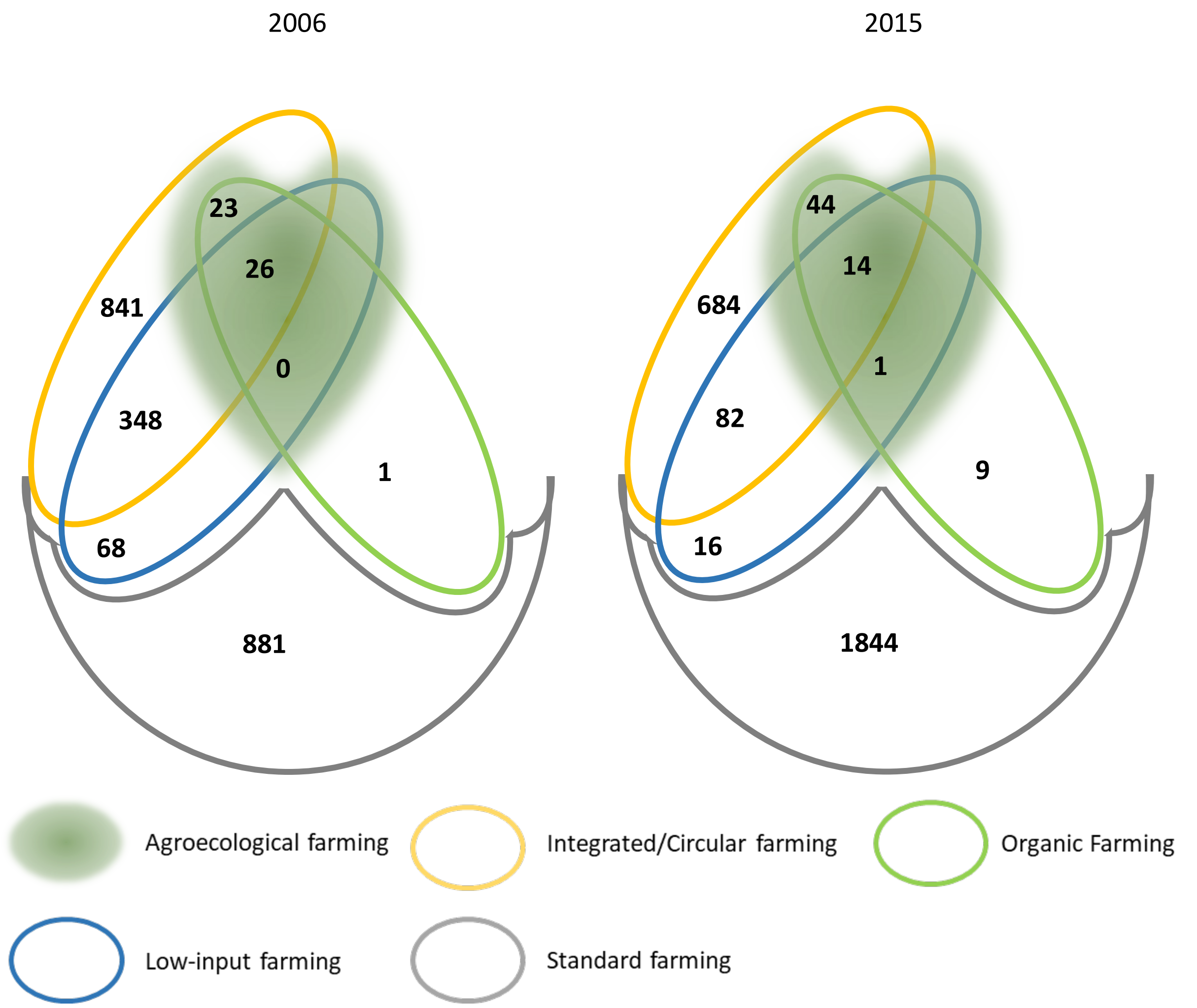


Figure 1: Poland's dairy farms according to their degree of ecological approaches based on LIFT FADN-protocol

Table 1: Structure and dynamics of Poland's dairy farms according to their degree of ecological approaches based on LIFT FADN-protocol

YEAR	ST		INT		INT-ORG		LI		LI-INT		LI-INT-ORG		LI-ORG		ORG		Annual total	
	No	%	No	%	No	%	No	%	No	%	No	%	No	%	No	%	No	%
2006	881	40.3	841	38.4	23	1.1	68	3.1	348	15.9	26	1.2	0	0.0	1	0.0	2188	100
2007	1087	47.6	797	34.9	24	1.0	40	1.7	308	13.5	29	1.3	0	0.0	1	0.0	2286	100
2008	1533	62.3	701	28.5	38	1.5	20	0.8	138	5.6	24	1.0	1	0.0	5	0.2	2460	100
2009	1461	58.0	731	29.0	24	1.0	25	1.0	239	9.5	33	1.3	2	0.1	4	0.2	2519	100
2010	1236	53.8	791	34.4	31	1.3	28	1.2	173	7.5	32	1.4	1	0.0	5	0.2	2297	100
2011	1344	60.0	706	31.5	40	1.8	16	0.7	105	4.7	21	0.9	2	0.1	6	0.3	2240	100
2012	1451	65.6	609	27.5	43	1.9	11	0.5	72	3.3	18	0.8	2	0.1	6	0.3	2212	100
2013	1684	64.9	726	28.0	59	2.3	14	0.5	78	3.0	21	0.8	1	0.0	12	0.5	2595	100
2014	1835	69.7	643	24.4	51	1.9	18	0.7	66	2.5	15	0.6	0	0.0	4	0.2	2632	100
2015	1844	68.4	684	25.4	44	1.6	16	0.6	82	3.0	14	0.5	1	0.0	9	0.3	2694	100
Total	14356	59.1	7229	30.2	377	1.5	256	1.1	1609	6.9	233	1	10	0.1	53	0.2	24123	-

Note: ST – standard, INT- integrated, LI- low-input, ORG-organic, the other are mix types of the basic four. Source: own calculations based on WP1 FADN protocol (Rega et al., 2021).

3.10.2.2 Comprehensive efficiency analyses by degree of ecological approaches

In the second step, we applied a nonparametric DEA-based methods for individual degrees of ecological approaches and for all groups together by applying: 1) Färe-Primont productivity change index (FPP) with its decomposition into technological change and efficiency changes for degrees of ecological approaches (Färe and Primont, 1995), and 2) Meta frontier Färe-Primont index for all degrees of ecological approaches following calculation procedures proposed by Dakpo *et al.*, (2016) and O'Donnell (2010).

The efficiency change (EC) of the Färe-Primont index was further decomposed into the product of three elements – technical efficiency change (TEC), scale efficiency (SEC) change and residual mix efficiency change (RMEC). Usually, the decomposition is written separately for input- vs. output-oriented productivity changes (O'Donnell, 2010), however Dakpo et al. (2016) proposes an expression to account for both orientations simultaneously, which in practice is a geometric mean, as we applied here.

In our analyses, decision making units (DMUs) which are farms that belong to different groups according to their degree of ecological approaches (standard, integrated, low-input, organic and mixed), so it is reasonable to believe that they have distinct technologies. In that case, as suggested by Dakpo et al. (2016), it is also appropriate to estimate a meta-technology which would grasp all groups' technologies (O'Donnell, Rao and Battese, 2008; Battese, Prasada Rao and O'Donnell, 2004; Battese and Rao, 2002).

Comparing the points of maximum productivity on the individual group frontiers (for each farm type) with that of the meta-frontier (for all farm types together), we obtain the technology gap ratios (TGR) and their changes (TGRC) as suggested by O'Donnell and Fallah-Fini (2011) and Dakpo et al. (2016). TGR measure the difference between each group frontier and meta-frontier and assesses which groups are leading in shifting the meta-frontier.

3.10.2.3 Common indicators of efficiency performance

In addition to the comprehensive and dynamic efficiency analyses described in 2.2 we calculated 10 technical-economic performance (TE) indicators based on FADN dataset for diary sector. The first four indicators from TE1 to TE4 are measures of profitability, the following four, from TE5 to TE8 are measures of partial productivity, and last two additional indicators are TE9 for market orientation and TE10 for equity ratios. They were calculated according to the following formulas in Table 2:

Table 2: Technical-economic indicators

Indicator	Description
T1	(private revenue-cost-ratio not considering remuneration of owned production factors) as SE131 / (SE275 + SE360 + SE370 + SE375 + SE380).
T2	(public revenue-cost-ratio not considering remuneration of owned production factors) as (SE131 + SE605) / (SE275 + SE360 + SE370 + SE375 + SE380).
T3	(private revenue-cost-ratio considering remuneration of owned production factors) as SE131 / (SE275 + SE360 + SE370 + SE375 + SE380 + (SE436 * imputed interest) + SE015 * hours per year of AWU in respective country + (SE025-SE030) * (SE030/ILNDRNT_V)), where: Inputted interest = 1.125, which is 75% of national reference interest rate of 2015-2020; hours per year of AWU in Poland in 2015 – 2120.
T4	(public revenue-cost-ratio considering remuneration of owned production factors) as (SE131 + SE605) / ((SE275 + SE360 + SE370 + SE375 + SE380) + (SE436 * 1.125) + SE015 * hours per year of AWU in respective country + (SE025-SE030) * (SE030/ILNDRNT_V)), where hours per year of AWU in Poland in 2015 – 2120.
T5	(partial productivity indicator, describing output per unit of the input land) as SE131 / SE025.
T6	(average product of labour) as SE131 / (SE010 * hours per year of AWU in respective country), where hours per year of AWU in Poland in 2015 – 2120.
T7	(average product of capital) as SE131 / (SE436 - ALNDAGR_CV) (= closing value of agricultural land).
T8	(average product of intermediary expenses) as SE131 / SE275.
T9	(market orientation) as SE131 / (SE131 + SE605).
T10	(equity ratio) as SE501 / SE436.

Note: calculations for imputed interest come from National Bank of Poland (Narodowy Bank Polski, 2021) based on interest rates from 1998-2020, https://www.nbp.pl/homen.aspx?f=/en/dzienne/stopy_archiwum.htm (accessed on 7 April 2021).

In order to compare the technical-economic farm performance along the degree of ecological approaches we applied the t-tests for the comparison of the means for ten TE indicators across all 8 ecological types based on FADN protocol (based on WP1 as before). So for each ecological type we checked if the mean for each indicator is significantly different from the values in other types, with significance level at 1%, 5% and 10%.

3.10.3 Data

In our quantitative analyses we use a farm-level data from the EU Farm Accountancy Data Network for Polish farms for the years 2004-2015, however for calculations we used the years 2006-2015, because the first two years of FADN were not fully operational for our analyses due to inconsistency with later data (the FADN was gradually developed from 2004 of Poland's accession to EU). Our initial FADN sample consisted of approximately 12 thousand farms per year (in 2015 it was 12,311 farms), representing over 730 thousand Polish farms with an annual standard output above 4,000 EUR, all combined providing 93% of total agricultural production in Poland (Floriańczyk *et al.*, 2019).

For our analyses we considered various variables characterising inputs and outputs of the farms. At the end after the analyses of their functional forms we selected four types of inputs defined as follows: 1) farm total utilised area in hectares (UAA) (FADN code SE025); 2) the labour force expressed in annual working units (AWU) (code SE010); 3) intermediate consumption in the Polish currency (PLN) (code SE275); and 4) capital in PLN (code SE436-SE446). As for the output, a single variable was used (also for the sake of the meta-frontier calculations), which is the value of the farm's total output in PLN (code SE131).

Table 3: Descriptive statistics for the Polish FADN dairy farms used for Färe-Primont analysis, 2006-2015

Type of farm; number of observations	Min	Max	Mean	Standard deviation	Coefficient of variation
All types together; no. of observations: 3140					
UAA [ha]	4.72	131.02	31.62	20.68	0.65
Labour [AWU]	0.70	9.22	2.10	0.70	0.33
Intermediate Consumption (PLN)	1963.17	326968.27	25843.46	26578.88	1.03
Capital [PLN]	12751.15	1065869.78	151784.68	128481.01	0.85
Total output [PLN]	2529.69	514420.03	51444.48	50180.18	0.98
Type Standard; no. of observations: 1050					
UAA [ha]	7.77	131.02	37.46	23.65	0.63
Labour [AWU]	1.12	9.22	2.31	0.85	0.37
Intermediate Consumption (PLN)	5794.89	326968.27	42722.28	35548.07	0.83
Capital [PLN]	38169.70	1065869.78	230039.99	158373.93	0.69
Total output [PLN]	10149.11	514420.03	84051.02	64646.07	0.77
Type Integrated; no. of observations: 70					
UAA [ha]	11.68	85.80	28.53	21.11	0.74
Labour [AWU]	1.28	3.00	2.02	0.48	0.24
Intermediate Consumption (PLN)	2031.65	29422.53	11481.39	6520.99	0.57
Capital [PLN]	23413.85	135307.17	73269.31	33886.39	0.46
Total output [PLN]	4243.94	59600.77	21853.48	12328.31	0.56
Type LowInput-Integrated; no. of observations: 10					
UAA [ha]	44.69	48.71	46.47	1.84	0.04
Labour [AWU]	1.76	2.20	1.99	0.12	0.06
Intermediate Consumption (PLN)	8653.74	15145.10	12546.99	1832.70	0.15
Capital [PLN]	89729.43	107468.10	99741.65	6438.72	0.06
Total output [PLN]	31244.38	44743.59	37930.86	4230.90	0.11
Type Mixed; no. of observations: 20					
UAA [ha]	18.13	19.71	19.12	0.45	0.02
Labour [AWU]	0.70	3.53	2.07	1.11	0.53
Intermediate Consumption (PLN)	5034.76	15158.02	8332.06	2971.48	0.36
Capital [PLN]	35944.15	185457.91	102159.14	58474.69	0.57
Total output [PLN]	6264.12	37977.03	18823.15	10833.01	0.58
Type Changeables; no. of observations: 1990					
UAA [ha]	4.72	127.32	28.70	18.30	0.64
Labour [AWU]	0.86	5.27	1.99	0.57	0.29
Intermediate Consumption (PLN)	1963.17	133138.76	17685.56	14786.42	0.84
Capital [PLN]	12751.15	705639.66	114016.32	88516.47	0.78
Total output [PLN]	2529.69	267776.14	35676.67	30181.95	0.85

Where: UAA - Total Utilised Agricultural Area [ha], (SE025); Labour -Total labour input [AWU] (SE010); Total intermediate consumption [PLN] (SE275); Capital: total assets - land, permanent crops & quotas [PLN] (SE436-SE446); Total Output [PLN] (SE131). Source: own calculations based on the Polish FADN.

The application of the Färe-Primont index based analyses required special data procedures. First the balanced panel of farms was needed so that the same farms repeated in the sample for all 10 years.

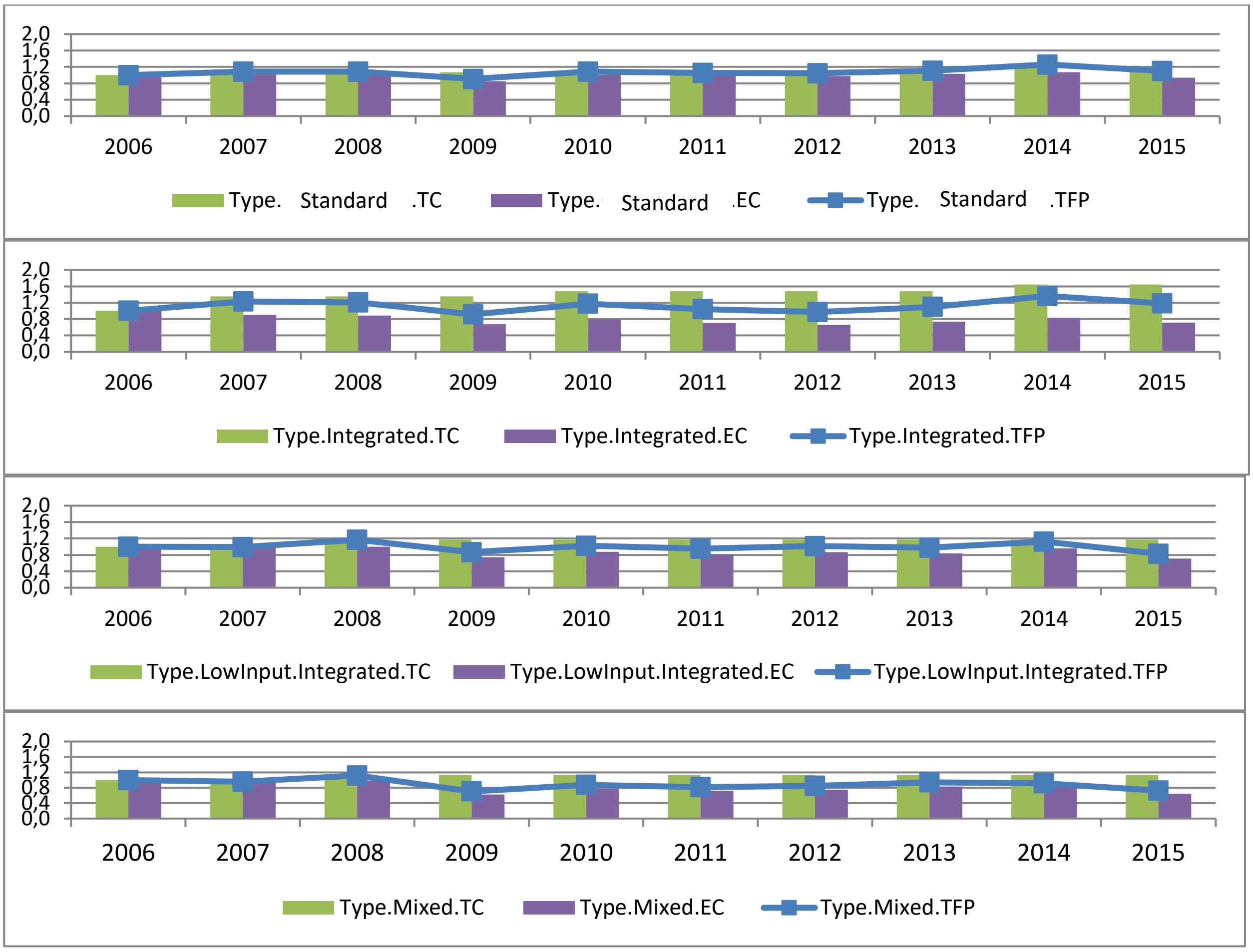
Second, as the method is sensitive for outliers so the special procedures were applied to remove such observations according to the procedures proposed by Dakpo et al. (2016).

As a result the data set was smaller but more consistent and homogeneous, and resulted in 5 types of ecological approaches because due to insufficient number of observations for econometric analyses some types needed to be aggregated. So the final set for which the results were generated is: 1) standard (ST), 2) Integrated (INT), 3) Lowinput-Integrated (LI-INT), 4) Mixed (MX) that is aggregation of INT-ORG, LI-INT-ORG, LI-ORG, LI and ORG, and 5) Changeable (CHB) that are the farms which changed their type of ecological approach over 10 years. The descriptive statistics for the final set of data is presented in Table 3.

3.10.4 Results

3.10.4.1 Results with separate frontiers by types of ecological approaches

The average TFP change indices at the year 2015 indicate the TFP change over the period 2006-2015. So there was TFP growth (values above 1) in case of standard, integrated and changeable farms but TFP decline in case of lowinput-integrated and mixed farms – see Figure 2. The highest growth was in case of integrated farms (18.1%), followed by standard (10.4% TFP growth) and changeable (4.3%). The TFP decline was higher for mixed ecological types (by 27.3%) than for lowinput-integrated (by 17.2%). It is also visible that all ecological types were affected by the global crises which appeared at the end of 2008, so they all experience the TFP decline in 2009 – see Figure 2.



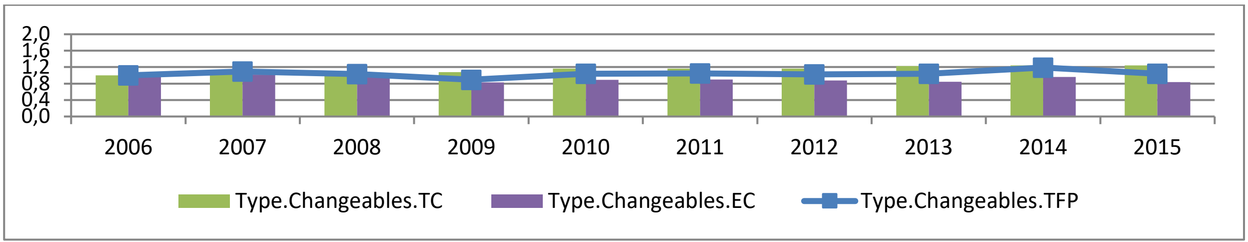


Figure 2: Färe-Primont productivity change and its decomposition, separate frontiers per ecological type. Source: own calculations based on the Polish FADN.

For all ecological farm types the technological change (TC) was positive while the efficiency change (EC) was negative for all the types. TC was the strongest driving force of the TFP growth in case of integrated farms (TC increased by 64.3%), changeables (TC growth by 24.2%) and standard farms (17.9%). In case of lowinput-integrated the TC was similar to standard farms (TC growth by 16.8%) however the decline in efficiency was so large (EC dropped by about 30%) that the TFP declined as well, opposite to the case of standard farms where TC growth was higher than EC decline. The highest decline in efficiency (EC) was in case of ecologically mixed farms, by 35.5% - see Figure 2. The fact that in all ecological types the technological change was going in opposite direction to efficiency development is an expected outcome justified in literature by the fact that not all producers can instantly adjust to new technology (Brümmer, Glauben and Thijssen, 2002; Latruffe, Fogarasi and Desjeux, 2012; Dakpo *et al.*, 2016).

Further decomposition of efficiency changes (EC) into technical efficiency change (TEC), scale efficiency change (SEC) and residual mix efficiency change (RMEC) was calculated. It shows that in case of standard farms the positive contribution to efficiency changes between 2005-2015 stem mainly from residual mix efficiency (increase by 12.2%) and scale efficiency (increase by 2.1%). So the farms managed to exploit their returns to scale factor and change other than only strictly farming practices (e.g. managerial, etc.). In case of integrated farms all three components of efficiency deteriorated – the technical and scale efficiency in similar magnitude (by c.a. 6.5%) while residual mix efficiency by more than that (17.7%). Lowinput-integrated farms maintained their technical efficiency over the period but their scale efficiency substantially dropped (by 24.4%). Mixed and changeable farms experienced similar decline in technical efficiency (which means deterioration in their farming practices, however their development of scale and residual efficiency changes were diametrically different. Changeable farms made up for this decline by a slight positive development in their SEC and RMEC (by 0.08% and 0.05% respectively) while mixed farm experience both efficiencies declining (by 2.8% and 23.1% respectively).

3.10.4.2 Results with meta-frontier

When all ecological types are taken together we can see that the dairy sector in Poland experienced over the decade 2006-2015 a slight TFP growth (3.5%), mostly due to progress in technological change (24.3%), while efficiency actually declined (-16.7%). That decline was mainly due to deterioration in technical efficiency (by 18%) while scale efficiency slightly improved (1.8%) and residual mix efficiency almost has not changed (the value is close to 1) – see Table 4.

Table 4: Average TFP changes and its component for the Polish FADN dairy farms, using meta-frontier for all ecological farm types

Years	TFP change (TFP)	Technological change (TC)	Efficiency change (EC)	Technical Efficiency change (TEC)	Scale Efficiency change (SEC)	Residual Mix Efficiency change (RMEC)
2006	1.000	1.000	1.000	1.000	1.000	1.000
2007	1.078	1.181	0.913	0.935	0.990	0.986
2008	1.013	1.181	0.858	0.880	1.001	0.974
2009	0.910	1.181	0.770	0.774	0.997	0.998
2010	1.035	1.181	0.876	0.880	0.997	0.999
2011	1.018	1.181	0.862	0.876	0.994	0.990
2012	1.002	1.181	0.849	0.849	1.003	0.997
2013	1.032	1.181	0.873	0.871	1.007	0.995
2014	1.184	1.243	0.953	0.928	1.025	1.003
2015	**1.035**	**1.243**	**0.833**	**0.820**	**1.018**	**0.998**

Source: own calculations based on the Polish FADN.

The results of meta-frontier by ecological farm types reveals that the meta-technology is mainly made of standard farms (which have the highest TGR of 0.998) so they mostly form the frontier – see Table 5. It is not surprising as they have access to the most productive technologies without ecological constraints. However, it is interesting that very close to them are farms with changeable ecological practices (TGR equals 0.928). The least productive technology is the one associated with group of ecologically mixed farms with TGR equal to 0.356, indicating that those farms reach only 35.6% of the maximum productivity that is feasible under the meta-technology.

Table 5: Technology gap ratios for the Polish FADN dairy farms, 2006-2015

Ecological types	TGR average
Standard	0.998
Integrated	0.545
LowInput-integrated	0.635
Mixed	0.356
Changeables	0.928

Source: own calculations based on the Polish FADN.

The changes of TGR over the years 2006-2015 (Table 6) show that standard farms are slightly losing their position as a leader of the technology in favour of changeable farms (TGR change for the former is slightly negative while for the latter it is +1.2%). Integrated farms which had only 54.5% of the overall meta-technology (Table 4) show however some signs of catching up with the technology experiencing the positive TGRC of 7.7%. Lowinput-integrated farms which have a bit less than halfway to the meta-frontier (TGR of 63.5%) did not change that position over the decade (TGRC equal 1). Mixed farms are not only the farthest from the meta-frontier, but their situation was also deteriorating (as TGRC decline by 16.2%) especially last two years of analysed period.

Table 6: Technology gap ratio changes (TGRC) for the Polish FADN dairy farms by ecological farm types, 2006-2015

Years	Standard	Integrated	LowInput-Integrated	Mixed	Changeables
2006	1.000	1.000	1.000	1.000	1.000
2007	1.000	1.202	0.929	0.818	0.937
2008	1.000	1.118	1.278	1.065	1.028
2009	1.000	0.924	1.132	0.892	1.090
2010	0.993	1.000	1.051	0.835	1.090
2011	1.000	1.039	0.976	0.776	0.891
2012	0.987	0.967	0.996	0.878	1.090
2013	1.000	1.121	0.946	0.801	1.082
2014	1.000	1.199	0.941	0.694	0.889
2015	1.000	1.196	0.749	0.616	1.023
Average	0.998	1.077	1.000	0.838	1.012

Source: own calculations based on the Polish FADN.

3.10.4.3 Results of common indicators of technical-economic performance

Comparison of farm performance by all degrees of ecological approaches validated by t-tests comparing the means (Table 6) shows that the ecological farm groups the least significantly differ in terms of intermediary partial productivity (TE8), equity ratio (TE10) and partial productivity of capital (TE7) and most significantly differ in terms of market orientation (TE9), partial productivity of land (TE5), partial productivity of labour (TE6) and private profitability when remuneration of owned production factors is included (TE3).

Standard farms have significantly higher level of all technical-economic indicators, except for profitability measured by TE2, average product of intermediary expenses (TE8) and equity ratio (TE10) for which three the values are significantly lower. Organic farms, on the contrary, differ significantly only in terms of “market orientation” (TE9). That indicator is significantly lower for those farms than for the other types. That means that those farms rely less on public subsidies compared to private revenues than other farm types. At the same time, organic farms are not significantly different in terms of profitability and productivity indicators from the others. Integrated and lowinput-integrated farms show similar performance results, so their values for most of the TE indicators are significantly lower. Exceptions are: profitability measured by TE1 - for which lowinput-integrated have significantly higher value than integrated and other types of farms, as well as profitability measured by TE2 and equity ratio measured by TE10 - for which both farm types have significantly higher mean values. Interestingly, low-input type does not differ significantly from other ecological farm types in terms of partial productivity of capital (TE7) and intermediary partial productivity (TE8) as well as equity ratio (E10). Also lowinput-organic is not significantly different from other types in terms of profitability measured by TE4, partial productivity of capital (TE7) and equity ratio (TE10).

Table 7: Summary of t-test results for technical-economic indicators by ecological types, 2015 (FADN protocol)

Performance indicator	Type of farms	T1_ST	T2_INT	T3_INT-ORG	T4_LI	T5_LI-INT	T6_LI-INT-ORG	T8_ORG
TE1	t-value	-3.7651	5.8549	3.1297	0.08	-4.8789	-4.2542	-0.445
	Pr(|T| > |t|)	0.0002***	0.0000***	0.0018***	0.9363	0.0000***	0.0000***	0.6563
TE2	t-value	9.7447	-3.5575	-1.0712	-2.1934	-11.8856	-7.5968	-0.9339
	Pr(|T| > |t|)	0.0000***	0.0004***	0.2842	0.0284**	0.0000***	0.0000***	0.3504
TE3	t-value	-18.2599	14.9579	6.1679	2.4446	3.675	1.673	1.2827
	Pr(|T| > |t|)	0.0000***	0.0000***	0.0000***	0.0146**	0.0002***	0.0944*	0.1997
TE4	t-value	-11.4972	9.9708	4.9686	1.6323	0.7099	0.601	1.3
	Pr(|T| > |t|)	0.0000***	0.0000***	0.0000***	0.1027 *	0.4778	0.5479	0.1937
TE5	t-value	-29.5537	24.0621	5.7536	2.8182	7.9463	2.801	-0.1829
	Pr(|T| > |t|)	0.0000***	0.0000***	0.0000***	0.0049***	0.0000***	0.0051***	0.8549
TE6	t-value	-20.718	16.358	4.8924	2.7253	6.3314	2.7867	0.8375
	Pr(|T| > |t|)	0.0000***	0.0000***	0.0000***	0.0065***	0.0000***	0.0054***	0.4024
TE7	t-value	-11.8611	10.114	4.2477	1.1184	1.7915	1.3376	0.7161
	Pr(|T| > |t|)	0.0000***	0.0000***	0.0000***	0.2635	0.0733*	0.1811	0.474
TE8	t-value	3.7115	-0.0485	-0.0559	-0.2499	-6.6907	-6.3555	-1.0141
	Pr(|T| > |t|)	0.0002***	0.9613	0.9554	0.8027	0.0000***	0.0000***	0.3106
TE9	t-value	-35.6137	24.9315	9.9702	4.2919	10.9205	3.7837	3.5812
	Pr(|T| > |t|)	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0002***	0.0003***
TE10	t-value	3.4639	-2.5221	-0.9308	-0.2181	-2.3845	-0.532	1.4642
	Pr(|T| > |t|)	0.0005***	0.0117***	0.352	0.8274	0.0172**	0.5948	0.1433

Note: Two-sample t test with equal variances, unpaired – (experimental, excluded from the analysis), significance levels: *** at 1%, ** at 5% and * significant at 10%.

3.10.5 Discussion and conclusions

According to statistical data the ecological production in Poland in the dairy sector is declining in the past years. This was confirmed by the analysis of FADN data, which has shown that not only the share of certified ecological dairy farms is small, but these numbers are also small within all farm groups outlined according to LIFT classification of ecological approaches. What is more important – all key groups (integrated and low-input) have shown declining trends over the analysed timeframe, which means that utilisation of ecological and sustainable approaches in Polish dairy farming is not gaining popularity.

Over the period of 2006-2015 a TFP growth was revealed in case of standard, integrated and changeable farms, yet a decline in case of lowinput-integrated and mixed farms. The highest growth was in case of integrated farms, followed by standard and changeables. The TFP decline was higher for mixed ecological types compared for lowinput-integrated. It is also visible that all ecological types were affected by the global crises which appeared at the end of 2008, so they all experience the TFP decline in 2009.

As far as the meta-frontier analysis is concerned, with all ecological types are taken together we can see that the dairy sector in Poland over the decade 2006-2015 experienced a slight TFP growth mostly due to progress in technological change, yet the efficiency declined. The decline was mainly due to deterioration in technical efficiency, while scale efficiency slightly improved with the residual mix efficiency almost not changing.

Key limitations to the analysis are the low number of farms implementing various ecological approaches, which results in limited confidence level of their data analysis, as well as has limited possibility of use as policy recommendation for farms implementing ecological approaches. On the other side, it is a precise reflection of the processes undergoing in the Polish dairy sector and are supported by the desk research data and interactions with stakeholders within LIFT workshops. Key issues blocking the development of ecological practices in farming dwell primarily within the economic and institutional dimensions.

Thus, the conclusions of the presented analysis can serve the policy makers in understanding what the current policies for Polish agricultural sector lack to contribute to achievement of the European sustainability goals, among other the European Green Deal targets. It is clear from the findings that the measures aimed at increasing the uptake of ecological approaches in Polish agriculture within the previous (2007-2013) and ongoing (2014-2020) Common Agricultural Policy have not been efficient enough, yet at the same time they did not target this issue to an extent that is understood now. Therefore, this needs to be considered in the next CAP programming period.

3.10.6 References

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3.11 Productivity and efficiency of pig and poultry farms differentiated by degrees of ecological approaches: the case of Poland (IRWiR PAN)

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3.11.1 Introduction and description of the case study

The sector of granivores consists of two major sections: pigs and poultry. As these differ to a great extent in both production processes, technologies and output, the analysis will be divided into the corresponding parts.

In regard to the in-depth analysis carried out, within the Polish FADN database in 2015 there were 755 granivore farms, yet only 4 had an ecological certificate and none were in the process of conversion. In 2006 this distribution was similar, yet the number of farms was 2.6 times higher: a total of 1,998 granivore farms, within which only 3 with a certificate and none in the conversion.

Currently the pig sector in Poland accounts 10.8 million heads (as of June 2019), which is the result of 29% decline since 2010 (GUS 2020). The share of Polish pig population within the EU equals 7.6%, placing Poland at 6th place (after Spain, Germany, France, Denmark and the Netherlands).

Information about ecological farms in this sector or their output is highly limited. According to Eurostat (2021) there were 4,189 head of organic pigs in 2019, which makes 0.04% of the total pig population kept by Polish farms. Eurostat (ORG_APROD parameter) and Statistics Poland (the official Polish statistics service) lack data on organic pig meat production whatsoever.

The poultry sector is showing the most dynamic growth rates, as its produce is finding both permanent domestic and growing foreign demand. Currently Poland is the indisputable leader in production of poultry meat in the EU-27 with the output of 2,593 thousand tonnes produced in 2019. The same indicator in 2010 equalled 1,342 thousand tonnes, meaning the growth rate reached 93.2% within nine years. Poland is also the 6th largest producer of poultry eggs among all EU-27 member states (after France, Germany, Spain, Italy, and the Netherlands) with 657 thousand tonnes or 12,056 million units produced in 2019 (GUS 2020).

Information about ecological farms in this sector or their output is highly limited. According to Eurostat (2021) there were 405,405 laying hens (0.7% of the total) and 21,218 broilers (0.02%) at Polish farms in 2019. This shows the extremely small scale of ecological farming in the poultry sector.

3.11.2 Method

The methods proposed in the paper were used for: 1) dividing granivores farms into groups different in terms of their degree of ecological approaches, 2) assessing of each group's individual and aggregated productivity and efficiency performance during 10 years, 3) identifying possible drivers of TFP and efficiency changes. They methods are presented in the following four subsections.

3.11.2.1 Identification of farm types by degree of ecological approaches

In the first step, we applied the FADN protocol, developed by Rega et al. (2021), in order to distinguish the meaningful groups of granivore farms according to their degree of ecological approaches. We distinguished 8 ecological types - 4 basic: standard (ST), low-input (LI), integrated (INT), organic (ORG) and 4 mixed types (INT-ORG, LI-INT, LI-INT-ORG, LI-ORG) - see Figure 1 and Table 1.

We identified 8 ecological types of farms and their shares in the total sample of the granivores farms were over the years 2006-2015 on average as follows: standard (78%), integrated (18.3%), low-input (0.7%%), organic (0.4%) and for the mixed types low-input integrated (2.2%), integrated-organic (0.3%), low-input integrated organic (0.1%) and low-input organic (0.3%). We observed over that time a declining number of standard farms (from 1,013 to 638) and increasing number of organic farms (from 0 to 5 farms), however the shares of both types were increasing – for standard from 50.7% to 84.6% and for organic from 0% to 0.7%. In case of integrated farms, we observed a substantial decline in their number (873 to 92) and share (from 43.7% to 12.2%) between 2006-2015. Low-input farms also declined, however less dramatically - from 24 to 5 farms which means from 1.2% to 0.7%. Similarly, lowinput-integrated farms decline in numbers (81 to 13) and in structure (4.1% to 1.7%). Interestingly, there were no lowinput-organic farms over that period. For the remaining types, integrated-organic and lowinput-integrated-organic farms almost no changes were observed over that time both in number and structure.

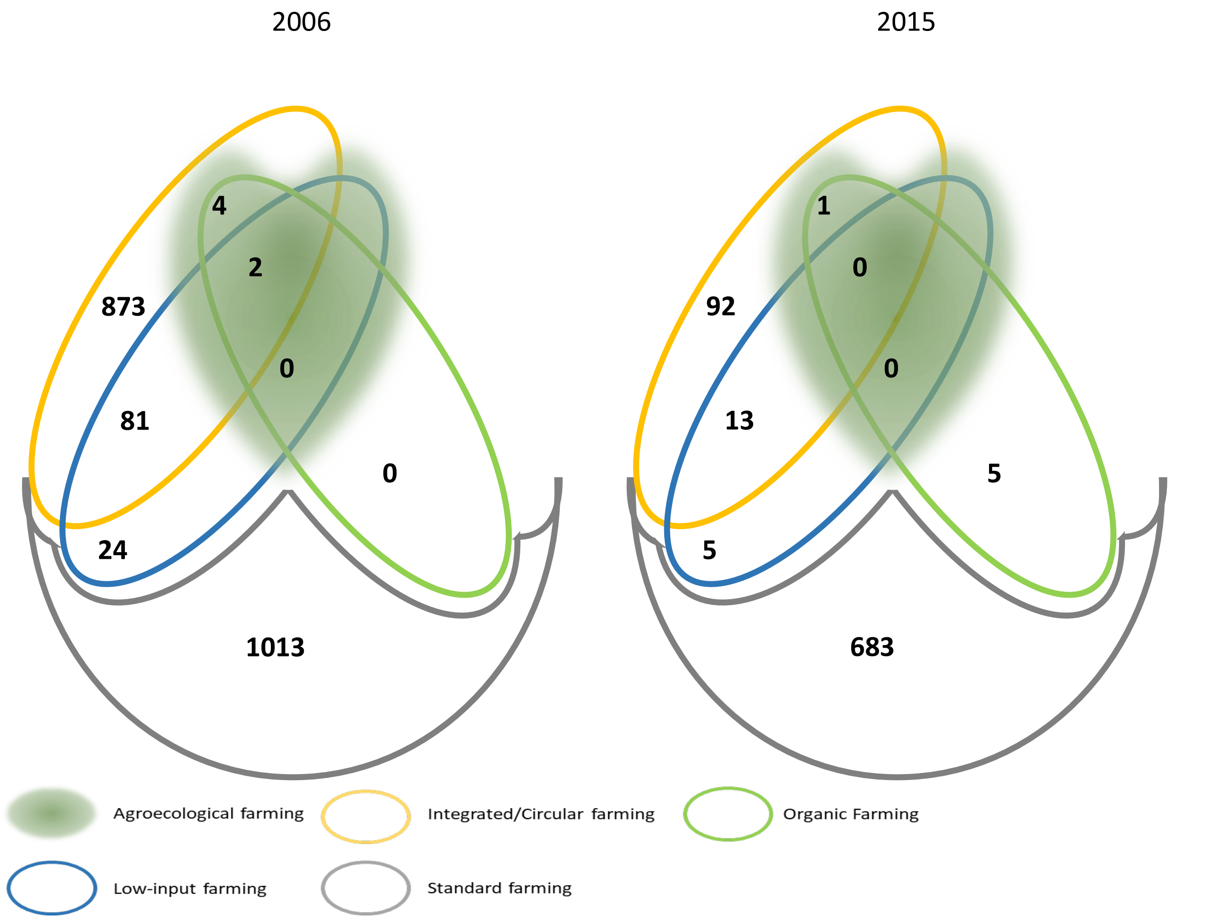

Figure 1: Poland's granivore farms according to their degree of ecological approaches based on LIFT FADN-protocol

Table 1: Structure and dynamics of Poland's granivore farms according to their degree of ecological approaches based on LIFT FADN-protocol

YEAR	ST		INT		INT-ORG		LI		LI-INT		LI-INT-ORG		LI-ORG		ORG		Total	
	No	%	No	%	No	%	No	%	No	%	No	%	No	%	No	%	No	%
2006	1013	50.7	873	43.7	4	0.2	24	1.2	81	4.1	2	0.1	0	0	0	0	1997	100
2007	1218	62.7	648	33.3	4	0.2	15	0.8	55	2.8	1	0.1	0	0	3	0.2	1944	100
2008	1446	84.5	232	13.6	4	0.2	9	0.5	13	0.8	0	0	0	0	8	0.5	1712	100
2009	807	80.9	159	15.9	2	0.2	11	1.1	14	1.4	0	0	0	0	4	0.4	997	100
2010	726	75.4	189	19.6	4	0.4	7	0.7	33	3.4	0	0	0	0	4	0.4	963	100
2011	682	80.4	131	15.4	5	0.6	6	0.7	20	2.4	0	0	0	0	4	0.5	848	100
2012	668	86.6	73	9.5	4	0.5	6	0.8	15	1.9	1	0.1	0	0	4	0.5	771	100
2013	718	86	91	10.9	3	0.4	5	0.6	13	1.6	1	0.1	0	0	4	0.5	835	100
2014	690	87.7	71	9	2	0.3	4	0.5	14	1.8	1	0.1	0	0	5	0.6	787	100
2015	638	84.6	92	12.2	1	0.1	5	0.7	13	1.7	0	0	0	0	5	0.7	754	100
Total	8606	78.0	2559	18.3	33	0.3	92	0.7	271	2.2	6	0.1	0	0.0	41	0.4	11608	-

Note: ST - is standard, INT- integrated, LI- low-input, ORG-organic, the other are mixed of those four. Source: own calculations based on WP1 FADN protocol (Rega et al., 2021).

3.11.2.2 Comprehensive efficiency analyses by degree of ecological approaches

In the second step, we applied a nonparametric DEA-based methods for individual degrees of ecological approaches and for all groups together by applying: 1) Färe-Primont productivity change index (FPP) with its decomposition into technological change and efficiency changes for different degrees of ecological approaches (Färe and Primont, 1995), and 2) Meta frontier Färe-Primont index for all degrees of ecological approaches following calculation procedures proposed by Dakpo *et al.*, (2016) and O'Donnell (2010).

The efficiency change (EC) of the Färe-Primont index was further decomposed into the product of three elements – technical efficiency change (TEC), scale efficiency (SEC) change and residual mix efficiency change. Usually, the decomposition is written separately for input- vs. output-oriented productivity changes (O'Donnell, 2010), however Dakpo et al. (2016) proposes an expression to account for both orientations simultaneously, which in practice is a geometric mean.

In our analyses, DMUs belong to different groups according to their degree of ecological approaches (standard, integrated, low-input, organic and mixed), so it is reasonable to believe that they have distinct technologies. In that case, as suggested by Dakpo et al. (2016), it is also appropriate to estimate a meta-technology which would grasp all groups' technologies (O'Donnell, Rao and Battese, 2008; Battese, Prasada Rao and O'Donnell, 2004; Battese and Rao, 2002).

Comparing the points of maximum productivity on the individual group frontiers (for each farm type) with that of the meta-frontier (for all farm types together), we obtain the technology gap ratios (TGR) and their changes (TGRC) as suggested by O'Donnell and Fallah-Fini (2011) and Dakpo et al. (2016) . TGR measure the difference between each group frontier and meta-frontier and assesses which groups are leading in shifting the meta-frontier.

3.11.2.3 Common indicators of efficiency performance

In addition to the comprehensive and dynamic efficiency analyses described in 2.2 we calculated 10 technical-economic performance (TE) indicators based on FADN dataset for diary sector. The first four indicators from TE1 to TE4 are measures of profitability, the following four, from TE5 to TE8 are measures of partial productivity, and last two additional indicators are TE9 for market orientation and TE10 for equity ratios. They were calculated according to the following formulas in Table 2:

Table 2: Technical-economic (TE) performance indicators

Indicator	Description
T1	(private revenue-cost-ratio not considering remuneration of owned production factors) as SE131 / (SE275 + SE360 + SE370 + SE375 + SE380).
T2	(public revenue-cost-ratio not considering remuneration of owned production factors) as (SE131 + SE605) / (SE275 + SE360 + SE370 + SE375 + SE380).
T3	(private revenue-cost-ratio considering remuneration of owned production factors) as SE131 / (SE275 + SE360 + SE370 + SE375 + SE380 + (SE436 * imputed interest) + SE015 * hours per year of AWU in respective country + (SE025-SE030) * (SE030/ILNDRNT_V)), where: Inputted interest = 1.125, which is 75% of national reference interest rate of 2015-2020; hours per year of AWU in Poland in 2015 – 2120.
T4	(public revenue-cost-ratio considering remuneration of owned production factors) as (SE131 + SE605) / ((SE275 + SE360 + SE370 + SE375 + SE380) + (SE436 * 1.125) + SE015 * hours per year of AWU in respective country + (SE025-SE030) * (SE030/ILNDRNT_V)), where hours per year of AWU in Poland in 2015 – 2120.
T5	(partial productivity indicator, describing output per unit of the input land) as SE131 / SE025.
T6	(average product of labour) as SE131 / (SE010 * hours per year of AWU in respective country), where hours per year of AWU in Poland in 2015 – 2120.
T7	(average product of capital) as SE131 / (SE436 - ALNDAGR_CV) (= closing value of agri-cultural land).
T8	(average product of intermediary expenses) as SE131 / SE275.
T9	(market orientation) as SE131 / (SE131 + SE605).
T10	(equity ratio) as SE501 / SE436.

Note that calculations for imputed interest come from National Bank of Poland (Narodowy Bank Polski, 2021) based on interest rates from 1998-2020, https://www.nbp.pl/homen.aspx?f=/en/dzienne/stopy_archiwum.htm (accessed on 7 April 2021).

In order to compare the technical-economic farm performance along the degree of ecological approaches we applied the t-tests for the comparison of the means for ten TE indicators across all 8 ecological types based on FADN protocol (based on WP1 as before). So for each ecological type we checked if the mean for each indicator is significantly different from the values in other types, with significance level at 1%, 5% and 10%.

3.11.3 Data

In our quantitative analyses we use a farm-level data from the EU Farm Accountancy Data Network for Polish farms for the years 2004-2015, however for calculations we used the years 2006-2015 because the first two years of FADN were not fully operational for our analyses due to inconsistency with later data (the FADN was gradually developed from 2004 of Poland's accession to EU). Our initial FADN sample consisted of approximately 12 thousand farms per year (in 2015 it was 12,311 farms), representing over 730 thousand Polish farms with an annual standard output above 4,000 EUR, and they provide 93% of total agricultural production in Poland (Floriańczyk et al., 2019). Out of this set we selected pig and poultry farms (granivores) which in TP14 nomenclature have code #50. Over the analysed period there were 11,608 of such farms.

For our analyses we considered various variables characterising inputs and outputs of the farms. At the end after the analyses of their functional forms we selected four types of inputs defined as follows: 1) farm total utilised area in hectares (UAA) (FADN code SE025); 2) the labour force expressed in annual working units (AWU) (code SE010); 3) intermediate consumption in the Polish currency (PLN) (code SE275); and 4) capital in PLN (code SE436-SE446). As for the output, a single variable was used (also for the sake of the meta-frontier calculations), which is the value of the farm's total output in PLN (code SE131) – see Table 3.

Table 3: Descriptive statistics for the Polish FADN granivores farms used for Färe-Primont analysis, 2006-2015

Type of farm; number of observations	Min	Max	Mean	Standard deviation	Coefficient of variation
Type Standard; no. of observations: 780					
UAA [ha]	5.20	138.67	31.38	21.99	0.70
Labour [AWU]	0.54	6.41	2.08	0.89	0.43
Intermediate Consumption (PLN)	6564.78	366326.35	74283.37	67667.83	0.91
Capital [PLN]	12202.15	1394295.71	195272.84	186627.78	0.96
Total output [PLN]	8212.24	457595.16	109203.91	96323.03	0.88
Type Integrated; no. of observations: 20					
UAA [ha]	23.33	38.04	32.07	4.57	0.14
Labour [AWU]	1.45	1.95	1.71	0.14	0.08
Intermediate Consumption (PLN)	19612.99	34406.92	27082.35	4776.43	0.18
Capital [PLN]	84349.94	238023.00	141905.12	44607.74	0.31
Total output [PLN]	33660.56	60164.55	47967.41	7720.37	0.16
Type Changeables; no. of observations: 1140					
UAA [ha]	5.44	481.71	32.52	43.57	1.34
Labour [AWU]	0.74	16.90	2.08	1.06	0.51
Intermediate Consumption (PLN)	5648.69	880973.81	63598.34	82999.25	1.31
Capital [PLN]	15192.14	1564824.01	182883.15	185708.99	1.02
Total output [PLN]	6184.04	1452603.40	97747.55	123977.96	1.27
All types together; no. of observations: 1940					
UAA [ha]	5.20	481.71	32.06	36.19	1.13
Labour [AWU]	0.54	16.90	2.08	0.99	0.47
Intermediate Consumption (PLN)	5648.69	880973.81	67517.93	77011.51	1.14
Capital [PLN]	12202.15	1564824.01	187442.12	185282.29	0.99
Total output [PLN]	6184.04	1452603.40	101840.52	113219.26	1.11

Where: UAA - Total Utilised Agricultural Area [ha], (SE025); Labour -Total labour input [AWU] (SE010); Total intermediate consumption [PLN] (SE275); Capital: total assets - land, permanent crops & quotas [PLN] (SE436-SE446); Total Output [PLN] (SE131). Source: own calculations based on the Polish FADN.

The application of the Färe-Primont index based analyses required special data procedures. First the balanced panel of farms was needed so that the same farms repeated in the sample for all 10 years. Second, as the method is sensitive for outliers so the special procedures were applied to remove such observations according to the procedures proposed by Dakpo et al. (2016). As a result, the data set was smaller than the initial one (1,940 farms) but more consistent and homogeneous, and resulted in 3 types of ecological approaches because due to insufficient number of observations for econometric analyses some types needed to be aggregated. So the final set for which the results were generated is: 1) standard (ST), 2) Integrated (INT), and 3) Changeables (CHB) – the last category are the farms which changed their degree of ecological approaches over 10 years. The descriptive statistics for the final set of data is presented in Table 3.

3.11.4 Results

3.11.4.1 Results with separate frontiers by degree of ecological approaches

The TFP changes over the whole period 2006-2015 for each farm type are expressed by indices from 2015 – see Figure 2. So we can see that there was TFP growth (values above 1) in case of standard and changeable farms, but there was a TFP decline in case of integrated farms. The highest TFP growth was in case of changeable farms (18.7%), followed by standard (8.6% TFP growth), while integrated farms experience TFP decline (- 25.4%). It is interesting to see that the global crises of 2008 affected the farm types in different way – TFP dynamics of standard farms seemed not to be much affected, the changeless experience slow down over the consecutive years (from 2009-2011) and integrated experienced deeper shock in 2009 and quick recovery in 2010-2011 – see Figure 2.

For all ecological farm types the technological change (TC) was positive. On the contrary, the efficiency change (EC) was negative - for standard and integrated types –and almost not changed for changeables (TFP close to 1). Usually, the technological change is going in opposite direction to efficiency development which indicates that not all producers can instantly adjust to new technology (Brümmer, Glauben and Thijssen, 2002; Latruffe, Fogarasi and Desjeux, 2012; Dakpo *et al.*, 2016). So interestingly, in case of changeables most of the farms were able to catch up with the advancement in the technology. TC was the strongest driving force of the TFP growth in case of standard farms (TC increased by 28.6%), and it was smaller but similar for the other two types - for integrated (TC growth by 19.1%) and changeables (18.5%). The highest decline in efficiency (EC) was in case of integrated farms, by 37.4%, and smaller in case of standard farms by 15.6% - see Figure 2.

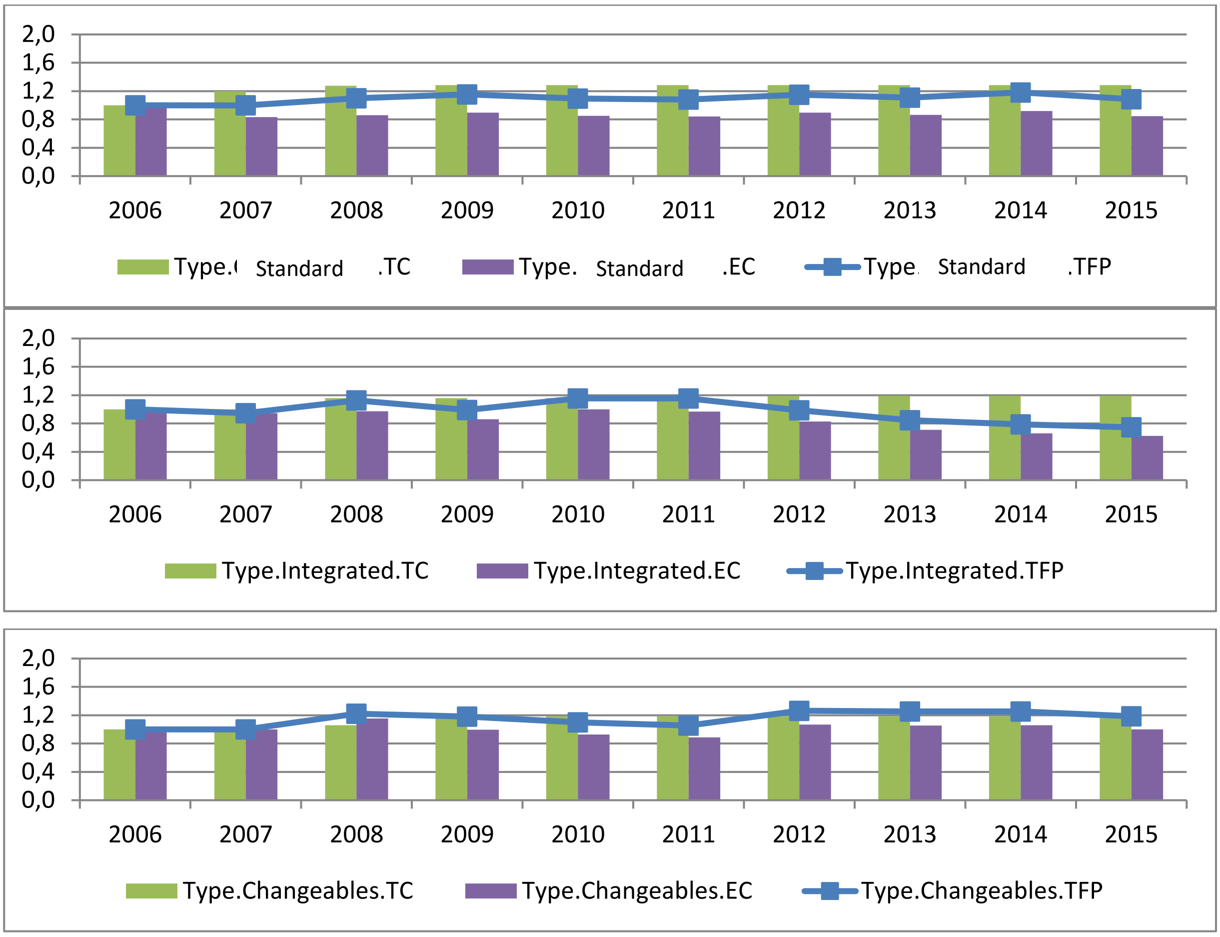

Figure 2: Färe-Primont productivity change and its decomposition, separate frontiers per ecological type for granivores. Source: own calculations based on the Polish FADN.

We decomposed the efficiency changes (EC) into technical efficiency change (TEC), scale efficiency change (SEC) and residual mix efficiency change (RMEC). The results are presented in Figure 2. They show that between 2005-2015 the changeable farms were most successful in maintaining their efficiency change. They managed to do so mainly due to substantial improvement in their residual mix efficiency (by 21.4%), that means improvement in other than farming practices. The improvement was big enough to overcome the substantial decline in technical efficiency (by -15.7%) stemming from deterioration in farming practices and a slight decline in scale efficiency (by -2.2%). Contrary, standard farms were not successful in maintaining their efficiency and it declined mainly due to decline in technical efficiency (by -17.1%) and scale efficiency (by -1.5%) despite that their residual mix efficiency increased slightly (by 3.5%). In case of integrated farms all three components of efficiency deteriorated by similar value - the technical efficiency by -11.9%, scale efficiency by -15.8% and residual mix efficiency by -15.6%. As for reaction of the farms to global financial crises of 2008, visible in statistics for 2009, it seems that changeable did the best, followed by standard farms while the most affected were integrated farms. However, since 2010 all recovered primarily due to technological change.

3.11.4.2 Results with meta-frontier

When all ecological farm types are taken together we can see that the granivores sector in Poland experienced between 2006-2015 a TFP growth by 9.6%, and it was mostly due to progress in technological change (26.8%), while efficiency declined (by -13.6%). That decline was mainly due to deterioration in technical efficiency (by -17.4%) and scale efficiency (by -10%) while the residual mix efficiency actually increased (by +5.8%) – see Table 4.

Interestingly, the results of meta-frontier by ecological farm types show that the meta-technology is mainly made of changeable farms not the standard farms. The former has the highest TGR of 0.943 while for the latter TGR is 0.939– see Table 5. It means that farm changing their ecological practices have access to more productive technologies than the standard farms in pig and poultry sector. Looking at the dynamics of the TGRs, it seems that changeables took over the lead from standard farms in the frontier since 2012. The least productive technology and very far from the frontier is the one for integrated farms with TGR equal to 0.409, indicating that those farms reach only about 41% of the maximum productivity that is feasible under the meta-technology. The dynamics show that actually the situation deteriorates rather than improve, and especially badly this type is doing since 2012.

Table 4: Average TFP changes and its component for the Polish FADN granivores farms, using meta-frontier for all ecological farm types

Years	TFP change (TFP)	Technological change (TC)	Efficiency change (EC)	Technical Efficiency change (TEC)	Scale Efficiency change (SEC)	Residual Mix Efficiency change (RMEC)
2006	1.000	1.000	1.000	1.000	1.000	1.000
2007	0.989	1.000	0.989	0.949	1.008	1.033
2008	1.116	1.206	0.925	0.977	1.023	0.925
2009	1.148	1.206	0.952	1.004	1.034	0.917
2010	1.064	1.206	0.882	0.935	1.031	0.914
2011	1.048	1.206	0.869	0.918	1.031	0.918
2012	1.175	1.268	0.927	0.890	1.001	1.040
2013	1.141	1.268	0.900	0.879	0.984	1.040
2014	1.178	1.268	0.929	0.887	1.000	1.046
2015	**1.096**	**1.268**	**0.864**	**0.826**	**0.990**	**1.058**

Source: own calculations based on the Polish FADN.

Table 5: Technology gap ratios (TGR) for the Polish FADN granivores farms, 2006-2015

Years	Standard	Integrated	Changeables
2006	0.886	0.412	1.000
2007	1.000	0.436	0.972
2008	1.000	0.360	0.877
2009	1.000	0.519	0.956
2010	1.000	0.509	0.833
2011	1.000	0.488	0.816
2012	0.749	0.332	1.000
2013	0.806	0.328	1.000
2014	1.000	0.367	0.975
2015	0.948	0.337	1.000

TGR Average	**0.939**	**0.409**	**0.943**

Source: own calculations based on the Polish FADN.

The dynamics of TGR change over the years 2006-2015 presented in Table 6 indicate that standard farms were strengthening their leadership position especially in the first half of that period so in general their TGRC showed positive development (increase by 6.0%).

The changeables on average showed negative dynamics of TGRC (-5.7%) which was mainly caused by substantial drop in their TGR in years after crises (-16.7% in 2010 and -18.4% in 2011). The average decline in TGRC of that sector was even worse than in case of integrated farms sector (for the latter the TGRC declined on average by -0.8%). However, despite those declines, changeables were on average at 94.3% level of meta-frontier while integrated farms at only 41%.

Table 6: Technology gap ratio changes (TGRC) for the Polish FADN granivores farms by ecological farm types, 2006-2015

Years	Standard	Integrated	Changeables
2006	1.000	1.000	1.000
2007	1.129	1.057	0.972
2008	1.129	0.875	0.877
2009	1.129	1.259	0.956
2010	1.129	1.235	0.833
2011	1.129	1.184	0.816
2012	0.845	0.806	1.000
2013	0.910	0.796	1.000
2014	1.129	0.891	0.975
2015	1.071	0.817	1.000
Average	**1.060**	**0.992**	**0.943**

Source: own calculations based on the Polish FADN.

3.11.4.3 Results of common indicators of technical-economic performance

We calculated 10 indicators of technical-economic performance for granivores farms by all 8 types of ecological approaches obtained from FADN protocol described in chapter *Identification of farm types by degree of ecological approaches* and validated by t-tests if their means are significantly different (see Table 7). The results show that all the farm groups do not significantly differ in terms of partial productivity of land (TE5) and equity ratio (TE10). Organic farms, in addition to those two indicators do not differ significantly from the others in terms of market orientation (TE9). Otherwise, organic farms have significantly higher values for all technical-economic indicators.

Table 7: Summary of t-test results for technical-economic indicators by ecological types for granivores, 2015 (FADN protocol)

Performance indicator	Type of farms	T1_ ST	T2_INT	T3_INT-ORG	T4_LI	T5_LI-INT	T6_LI-INT-ORG	T7_LI-ORG	T8_ORG
TE1	t-value	3.6274	-1.6803	.	-1.0524	-2.7334	.	.	-2.6907
	Pr(|T| > |t|)	0.0003***	0.0933*	.	0.2929	0.0064***	.	.	0.0073***
TE2	t-value	5.9391	-3.9433	.	-0.6227	-3.6228	.	.	-2.3452
	Pr(|T| > |t|)	0.000***	0.0001***	.	0.5337	0.0003***	.	.	0.0193**
TE3	t-value	-1.9588	3.8445	.	-2.1696	0.6333	.	.	-5.86
	Pr(|T| > |t|)	0.0505**	0.0001***	.	0.0304**	0.5267	.	.	0.000***
TE4	t-value	-1.5805	3.4921	.	-2.1178	0.5785	.	.	-6.1078
	Pr(|T| > |t|)	0.1144	0.0005***	.	0.0345**	0.5631	.	.	0.000***
TE5	t-value	0.1682	0.044	.	-0.2084	-0.4059	.	.	-0.1319
	Pr(|T| > |t|)	0.8665	0.9649	.	0.8349	0.6849	.	.	0.8951
TE6	t-value	-3.6554	5.1408	.	-2.4778	0.588	.	.	-3.0837
	Pr(|T| > |t|)	0.0003***	0.000***	.	0.0134**	0.5567	.	.	0.0021***
TE7	t-value	-1.7669	3.8426	.	-2.7654	0.3678	.	.	-5.8446
	Pr(|T| > |t|)	0.0776*	0.0001***	.	0.0058***	0.7131	.	.	0.000***
TE8	t-value	6.4467	-3.9012	.	0.0785	-5.4788	.	.	-1.5451
	Pr(|T| > |t|)	0.000***	0.0001***	.	0.9375	0.000***	.	.	0.1228
TE9	t-value	-7.9133	8.4334	.	-1.6082	2.3752	.	.	-1.1984
	Pr(|T| > |t|)	0.000***	0.000***	.	0.1082	0.0178**	.	.	0.2311
TE10	t-value	-0.3044	-0.362	.	1.2247	1.3704	.	.	-0.3289
	Pr(|T| > |t|)	0.7609	0.7174	.	0.2211	0.171	.	.	0.7423

Note: Note: Two-sample t test with equal variances, unpaired – (experimental, excluded from the analysis), significance levels: *** at 1%, ** at 5% and * significant at 10%. Source: own calculations.

Standard farms do not differ significantly from other farms, apart from TE5 and TE10 with respect to profitability indicator (TE4). Otherwise they have significantly higher values of TE2, TE3, TE6, TE7 and TE9 and significantly lower values for TE1 and TE8.

Integrated farms have significantly lower values of most of the indicators, i.e. profitability if remuneration of owned production factors is considered (i.e., TE3 and TE4), partial productivity of labour (TE6) and partial productivity of capital (TE7) as well as market orientation (TE9). On the other side integrated farms have significantly higher values of profitability measured by TE1 and TE2, that when the remuneration of owned production factors is not considered, and partial intermediary productivity (TE8).

Low-input farms do not significantly differ in terms of most of the indicators, and they have significantly higher values only for two profitability indicators taking into account remuneration of owned production factors (TE3 and TE4) as well as for two partial productivities, of labour (TE6) and capital (TE7).

Lowinput-integrated farms have significantly higher profitability indicators when no remuneration of owned production factors are included (TE1 and TE2) as well as for partial intermediary productivity (TE8). On the contrary, significantly lower values in this group are for market orientation (TE9).

Other mixed types (INT-ORG, LI-INT-ORG and LI-ORG) are not enough represented by farms to be able to compare the means.

All in all the granivores ecological farm groups the least significantly differ in terms of partial land productivity (TE5) and equity ratio (TE10) for other indicators they are rather significantly different for most ecological types of farms.

3.11.5 Discussion and conclusions

According to statistical data the ecological production in Poland in the pigs and poultry sector (combined in the report as the “granivores”) is drastically low. The share of pigs kept in certified ecological farms equals 0.07% of the total pig population, the share of laying hens – 0.7% and broilers – less than 0.02%. Among them the only type of livestock showing growth in the ecological output are the laying hens by manifesting a 52% growth of head numbers within 2017-2018.

These conclusions were confirmed by the analysis of FADN data, which has shown that not only the share of certified ecological dairy farms is extremely small, but these numbers are also drastically small within all farm groups outlined according to LIFT classification of ecological approaches. What is more important – all key groups (integrated and low-input) have shown declining trends over the analysed timeframe, which means that utilisation of ecological and sustainable approaches in Polish pigs and poultry farming is not gaining popularity. The only major group beside standard farms, being the integrated ones, has shrunk from 873 to 92 farms within 2006-2015.

Over the period of 2006-2015 a TFP growth (values above 1) was revealed in case of standard and changeable farms, but there was a TFP decline in case of integrated farms. The highest TFP growth was in case of changeable farms, followed by standard, while integrated farms experience TFP decline. It is interesting to see that the global crises of 2008 affected the farm types in different way – TFP dynamics of standard farms seemed not to be much affected, the changeless experience slow down over the consecutive years (from 2009-2011) and integrated experienced deeper shock in 2009 and quick recovery in 2010-2011.

As far as the meta-frontier analysis is concerned, with all ecological types are taken together we can see that the granivores sector in Poland experienced between 2006-2015 a TFP growth by 9.6%, and it was mostly due to progress in technological change, while efficiency declined. That decline was mainly due to deterioration in technical efficiency and scale efficiency, while the residual mix efficiency actually increased.

Key limitations to the analysis are the low number of farms implementing various ecological approaches, which results in limited confidence level of their data analysis, as well as has limited possibility of use as policy recommendation for farms implementing ecological approaches. On the other side, it is a precise reflection of the processes undergoing in the Polish granivores sector and are supported by the desk research data and interactions with stakeholders within LIFT workshops. Key issues blocking the development of ecological practices in farming dwell primarily within the economic and institutional dimensions.

Thus, the conclusions of the presented analysis can serve the policy makers in understanding what the current policies for Polish agricultural sector lack to contribute to achievement of the European sustainability goals, among other the European Green Deal targets. It is clear from the findings that the measures aimed at increasing the uptake of ecological approaches in Polish agriculture within the previous (2007-2013) and ongoing (2014-2020) Common Agricultural Policy haven't been efficient enough, yet at the same time they didn't target this issue to an extent that is understood now. Therefore, this needs to be considered in the next CAP programming period.

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3.12 Innovation and eco-system based drivers of total farm factor productivity: assessment based on LIFT large-scale survey (with emphasis on dairy and granivore farms in Poland) (IRWiR PAN)

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3.12.1 Introduction and description of the case study

Polish dairy sector is the 4th largest producer of raw milk among all EU-27 member states (after Germany, France and the Netherlands - Eurostat 2021), holding this position since the country's accession to the EU in 2004. The average annual growth rate of the output (raw milk delivered to the dairies) within 2005-2019 equals 2.4%, which consistently led to delivery of 10.9 million tonnes of milk in 2015 and 12.2 million tonnes in 2019. The total production of milk is even higher reaching 14.1 million tonnes in 2019 (GUS 2020).

The number of dairy cows shows a permanent decline trend, reaching 2.28 million heads in 2015 and 2.22 million heads in 2019 (compared to 2.8 million heads in 2004). Yet this decline is compensated by intensification of production processes and increasing productivity. Thus, the annual average production of milk per cow has grown from 4,082 litres in 2004 (GUS 2007) to the 5,803 litres in 2019 (GUS 2020).

The sector of granivores consists of two major sections: pigs and poultry (MRiRW 2016). Currently the pig sector in Poland accounts 10.8 million heads (as of June 2019), which is the result of 29% decline since 2010 (GUS 2020). The share of Polish pig population within the EU equals 7.6%, placing Poland at 6th place (after Spain, Germany, France, Denmark and the Netherlands).

The poultry sector is showing the most dynamic growth rates, as its produce is finding both permanent domestic and growing foreign demand. Currently Poland is the indisputable leader in production of poultry meat in the EU-27 with the output of 2,593 thousand tonnes produced in 2019. The same indicator in 2010 equalled 1,342 thousand tonnes, meaning the growth rate reached 93.2% within nine years. Poland is also the 6th largest producer of poultry eggs among all EU-27 member states (after France, Germany, Spain, Italy, and the Netherlands) with 657 thousand tonnes or 12,056 million units produced in 2019 (GUS 2020).

3.12.2 Method and data

Our quantitative analysis is based on information from a large-scale survey, carried within H2020 project LIFT in 2019, where 100 of the Polish farms were interviewed. The survey was very detailed, with hundreds of questions, focusing on very detailed farm practices and strategies in farm types differing with respect to their degree of ecological approaches. The questions referred, among the other, to innovations and ecosystem approaches.

We extracted information for 100 Polish farms in division into five farm types which are in the centre of our interest (i.e., field crop farms, horticulture, granivores, dairy and mixed farms). For those farm types we extracted information about the drivers of their total factor productivity (TFP) changes which according to Coomes *et al.*, (2019) stem from:

1) sources of innovations such as gene revolution, enhanced input delivery, hardware & software, post-harvest management – that is technological approach to TFP growth, and

2) adapted variety of ecosystem services such as biological pest control, pollinator management, integrated crop-livestock practices, rotation & soil conservation – that is ecosystem–based approach to TPF growth.

Following this approach we identified in our database 8 indicators within 4 categories of sources of innovations and 24 indicators within 4 categories for ecosystem services, presented below:

I. Sources of innovations:
1. Gene revolution:
   - I.1 Varieties tolerant of weeds.
2. Enhanced input delivery:
   - I.2 Precision technologies to target application rate.
   - I.3 Precision technologies to guide herbicide application.
3. Hardware, software and data:
   - I.4 Decision making tools to support management of precision technologies.
   - I.5 Machine controlled application.
   - I.6 Soil mapping.
4. Post-harvest management:
   - I.7 Leaving crop residues on soil.
   - I.8 Planting of catch crops.

II. Ecosystem services:
1. Biological pest control:
   - II.1 Pest/disease resistant/tolerant varieties.
   - II.2 Machine weeding.
   - II.3 Manual weeding.
   - II.4 Thermal weed control.
   - II.5 Integrated weed management (IWM) principles.
2. Pollinator management:
   - II.6 Hedgerows.
   - II.7 Bushes.
   - II.8 Wet areas.
   - II.9 Tree lines.
   - II.10 Woodland on UAA (coppice, afforested areas, woodlots, etc.).
   - II.11 Isolated trees.
   - II.12 Field margins.
   - II.13 Buffer strips.
   - II.14 Flower strips.
3. Integrated crop-livestock practices:
   - II.15 Application of animal manure on arable land.
   - II.16 Application of animal manure on pastures.
   - II.17 Presence of livestock.
   - II.18 Arable land for temporary grassland-type forage production, thereof.
   - II.19 permanent grassland area with pure meadows (only cut).
   - II.20 Permanent grassland area with pure pastures (only grazed).
4. Rotation and soil conservation:
   - II.21 Crop rotation.

II.22 Crop diversification.
II.23 Selection of traditional/locally adapted varieties.
II.24 Mixed cropping (including intercropping, alley cropping, relay cropping).

The statistics related to those indicators by farm types are presented in the Results section and they are further used for assessing the sources of technological change driving TFP among the groups of farms.

3.12.3 Results

Table 1 shows various innovations adopted by farm types, contributing to TFP change while Table 2 shows the ecosystem-services adopted by farm types contributing to TFP change. The farming sectors differ substantially in adoption of innovations, where the leading sector was dairy (with the highest percentage of farm adopting innovations) and second best granivores (with all the investigated ecosystem-based services present in the sector). The least innovating seem to be the mixed farms. However, also those less innovating farming sectors have in some cases high percentage of innovations adopted, e.g., varieties of tolerant weeds in case of field crop and horticulture, leaving crop residues on soil in field crop farms or planting of catch crops mixed farms – see Table 1.

Table 1: Innovation-based drivers of TFP changes (% of farms)

Drivers	Indicators	Field crop	Horticulture	Granivores	Dairy	Mixed
Gene revolution	Varieties tolerant of weeds	35	50	7	63	6
Enhanced input delivery	Precision technologies to target application rate	10	0	11	63	0
	Precision technologies to guide herbicide application	0	8	11	63	3
Hardware, software and data	Decision making tools to support management of precision technologies	0	0	7	63	0
	Machine controlled application	5	0	7	50	0
	Soil mapping	0	8	11	63	6
Post-harvest management	Leaving crop residues on soil	30	8	18	38	6
	Planting of catch crops	20	17	32	63	22

Source: own calculations based on LIFT large-scale farm survey of 100 Polish farms.

The farming sectors differ also substantially in adoption of ecosystem services – see Table 2. The leaders in our sample are dairy farms and granivores, as they have the highest percentages of farms adopting the practices in all categories – biological pest control, pollinator management, integrated crop-livestock practices, to rotation and soil conservation.

Table 2: Ecosystem based drivers of TFP changes (% of farms)

Drivers	Indicators	Field crop	Horticulture	Granivores	Dairy	Mixed
Biological pest control	Pest/disease resistant/tolerant varieties	60	33	14	88	22
	Machine weeding	40	67	36	75	56
	Manual weeding	45	42	36	100	47
	Thermal weed control	5	0	4	0	-
	Integrated weed management (IWM) principles	10	0	7	63	16
Pollinator management	Hedgerows	5	25	7	25	6
	Bushes	10	33	36	25	19
	Wet areas	10	0	11	0	13
	Tree lines	0	0	4	0	6
	Woodland on UAA (coppice, afforested areas, woodlots, etc)	0	0	11	13	13
	Isolated trees	40	33	61	63	56
	Field margins	55	33	43	50	66
	Buffer strips	5	8	4	0	0
	Flower strips	0	0	4	25	9
Integrated crop-livestock practices	Application of animal manure on arable land	75	58	100	100	88
	Application of animal manure on pastures	0	25	93	88	56
	Presence of livestock	30	25	100	88	91
	Arable land for temporary grassland-type forage production, thereof:	10	17	71	88	50
	(a) permanent grassland area with pure meadows (only cut)	55	8	39	75	63
	(b) Permanent grassland area with pure pastures (only grazed)	10	0	4	0	22
Rotation and soil conservation	Crop rotation	50	50	89	88	84
	Crop diversification	25	33	57	63	38
	Selection of traditional/locally adapted varieties	15	17	18	50	16
	Mixed cropping (including intercropping, alley cropping, relay cropping)	0	0	4	38	3

Source: own calculations based on LIFT large-scale farm survey of 100 Polish farms.

Over 80% of dairy farms declared application of pest/disease resistant/tolerant varieties (88%), manual weeding (100%), application of animal manure on arable land (100%) and pastures (93%), presence of livestock (88%), arable land for temporary grassland-type forage production (88%) and crop rotation (88%). Above 80% of granivore farms declared application of animal manure on arable land (100%)

and pastures (93%), presence of livestock and crop rotation (89%). Half or more of mixed farms declared machine weeding (56%), isolated trees (56%), field margins (66%), application of animal manure on arable land (88%) and pastures (56%), arable land for temporary grassland-type forage production (50%), presence of livestock (91%), permanent grassland are with pure meadows (63%) and crop rotation (84%). Most of the horticulture farms in our sample apply machine weeding (67%), application of manure on arable land (58%) and crop rotation (50%). Majority of field crop farms declare application of pest/disease resistant/tolerant varieties (60%), field margins (55%), application of animal manure on arable land (75%), permanent grassland areas with pure meadows, only cut (55%) and crop rotation (50%).

3.12.4 Discussion and conclusions

Various innovations adopted by farm types were analysed, contributing to TFP change, as well as the ecosystem-services adopted by farm types contributing to TFP change. The farming sectors differ substantially in adoption of innovations, where the leading sector was dairy (with the highest percentage of farm adopting innovations) and second best granivores (with all the investigated ecosystem-based services present in the sector). The least innovative seem to be the mixed farms.

However, also those less innovating farming sectors have in some cases high percentage of innovations adopted, e.g., varieties of tolerant weeds in case of field crop and horticulture, leaving crop residues on soil in field crop farms or planting of catch crops mixed farms.

Over 80% of dairy farms declared application of pest/disease resistant/tolerant varieties (88%), manual weeding (100%), application of animal manure on arable land (100%) and pastures (93%), presence of livestock (88%), arable land for temporary grassland-type forage production (88%) and crop rotation (88%).

3.12.5 References

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3.13 Environmentally-friendly practices and economic performance in dairy and beef cattle farming in France (INRAE and VetAgro Sup)

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3.13.1 Introduction

Scientific studies show that agroecological practices are essential to reduce the use of fertilisers, pesticides, antiparasitic and veterinary antibiotics, which have negative impacts on the environment and human health. More and more farmers are now implementing environmentally-friendly practices that enhance biodiversity and natural regulations, such as crop diversification, extensification of livestock farming, association between plant and animal production, enhancement and maintenance of grasslands, reduction in the size of plots, no-till, direct-sowing. Some researchers have carried out comparative reviews of technical, economic, social, or environmental performance of organic farming versus conventional farming and results are not clear-cut. In addition, studies comparing the performance between farms using one specific environmentally-friendly practice and those that do not, are limited.

In this context, the objective of this article is to contribute to this empirical literature and compare the economic performance of farms that apply a higher degree of environmentally-friendly practices and farms with a lower implementation of such practices. In what follows, as several practices will be considered separately, for clarity reason we will call the former 'ecological farms' and the latter 'non-ecological farms'. The application is to a sample of dairy and beef cattle specialist farms in France in 2018, whose data were collected through a specific survey.

3.13.2 Dairy and beef cattle farming in France

France was the main agricultural producing country in the European Union (EU) in 2018 (Eurostat, 2018). The French agricultural sector production value was about 76 billion Euros (without subsidies, that were close to 8 billion Euros), including crop production (46 billion Euros), animal production (26 billion Euros) and agricultural services (4 billion Euros). Within animal production, dairy and beef gross outputs amounted to 17 billion Euros, including 5.8 billion Euros for beef and dairy cows, 1.2 billion Euros for calves, and 10 billion Euros for milk. Dairy and beef cattle farms received direct animal subsidies from the CAP, amounting 643 million Euros for beef production and 93 million Euros for dairy production. These farming systems had 1 billion Euros veterinary expenses and 7 billion Euros in cost of concentrated feed.

In 2016, the farming population consisted in 430,000 farms and about 158,000 were dairy or beef cattle specialists. 45,000 were specialised in dairy production and 57,000 were specialised in beef meat production, while 8,000 farms produced both milk and beef meat and 48,000 were large livestock systems producing field crops and raising cattle for meat or milk production (Agreste, 2018). All these farms produced 24 million tons of cow's milk, a quantity that has stagnated over a long time, and 1.68

million tons carcass equivalent including 1.45 million adult cattle (live animals weighing more than 300kg) and 0.224 million calves. One of the particularities of the French beef production is that half of the calves of about 10 months old produced in France are exported (with a large majority - 72% - going to the Po Valley in Italy and 28% being fattened in Spain or Turkey), and the other half is fattened in Western and Eastern France (CNE and IDELE, 2016).

The majority of dairy and beef cattle farms in France are conventional farms, although the number of organic farms is continuously increasing (Agreste, 2019; Agence Bio, 2020). In general, in France (all productions together), there were in 2019 about 47,200 farms in organic farming, that is to say 10.4% of farms and 8.3% of the French utilised agricultural area (UAA). The latter has doubled over the past 5 years, from 1.1 million hectares (ha) in 2014 to 2.3 million ha in 2019. As regard cattle farms specifically, in 2019 there were 5,824 organic suckler cow farms breeding about 212,000 animals. This represented 5.3% of French suckling farms and 2% of the quantity of beef produced in France. One third of organic beef production was concentrated in three French regions: Pays-de-La-Loire (Western France), Midi-Pyrénées (Southern France) and Auvergne (Central France). As for organic dairy farms, they were 4,564 in 2019, with about 243,000 animals. This represented 4.2% of the French dairy farms and 4% of the quantity of milk produced in France.

In this study we consider several regions in France: (i) the four NUTS3 regions that make the NUTS2 region Brittany (Côtes d'Armor, Finistère, Ille-et-Vilaine, Morbihan), which is a plain area in Western France; (ii) NUTS3 region Sarthe which is also a plain area in Western France but on the East of Brittany; and (iii) NUTS3 region (Puy-de-Dôme) which is a mountainous region in central France.

3.13.3 Data

A specific survey was carried out to farmers in Brittany, Sarthe and Puy-de-Dôme (face-to-face or online) at the end of 2019 and beginning of 2020. The questionnaire collected economics and structural information on farms for the year 2018, as well as detailed information on practices (see Tzouramani et al., 2019). The contact details of farmers targeted by the survey were obtained from value chain stakeholders, namely processors, farmers' groups and local government. The sample used here consists in 159 farms specialist in dairy farming or beef cattle farming, or mixed dairy-beef cattle. The distribution of farms over the NUTS3 regions is as follows: Sarthe (13 farms), Côtes-d'Armor (21), Finistère (18), Ille-et-Vilaine (18), Morbihan (19) and Puy-de-Dôme (70). We report descriptive statistics of the sample used in Table 1.

Farms in the sample operate on average 115 ha of UAA and breed 111 livestock units for dairy and beef cattle. These figures are in line with the description of the regions in the previous section. Only 36% of the UAA is covered by permanent pasture on average. A low part of UAA is owned (34% on average), consistent with the low share of individual farms (26%): there are many partnership farms in the dairy and beef cattle sector, and the partners own land and rent it out to the partnership farm, thus explaining the high part of rented land. By contrast, family labour is still the majority on the farm (87% on average), which is in part explained by the need to be close to the animals days and nights. Almost one third (32%) of the farms are in high altitude (above 600 m), namely in Puy-de-Dôme, and more than one third (37%) are located in less favoured areas (LFA). The latter are areas with natural constraints such as mountains, and farmers receive subsidies from the Common Agricultural Policy (CAP) when their farm is located in these areas. All CAP operational subsidies (direct, coupled, AES and LFA subsidies) are on average 164 Euros per ha of UAA.

Table 1: Descriptive statistics of the sample

Characteristics	Unit	Mean	Coef. of variation
Age of the farmer	years	46.8	0.22
Experience of the farmer	years	23.78	0.47
Cattle herd size	Number of cattle livestock units	111	0.62
UAA	ha	115	0.63
Share of owned land in UAA	%	34	0.88
Share of permanent grassland in UAA	%	36	0.96
Farm labour	Number of weeks worked	114	0.42
Share of family labour in farm labour	%	87	0.23
Revenue from sales	Euros	260,102	0.95
CAP operational subsidies per ha of UAA	Euros per ha	164	0.74
		Share	
Share of male farmers		87%	
Share of farmers with university education (agricultural or not)		46%	
Share of individual farms		26%	
Share of farms specialists dairy		68%	
Share of farms with most of the farmland at 600 m or over		32%	
Share of farms in LFA		37%	
Share of farms in Natura 2000 area		15%	

3.13.4 Methodology

3.13.4.1 Identification of ecological and non-ecological farms

To identify ecological farms and non-ecological farms, that is to say farms that have adopted environmentally-friendly practices and farms that have not, we created five typologies, based on specific environmentally-friendly practices. In three typologies we rely on ecological nomenclatures that are well known and well accepted: certified organic farming; in conversion to organic farming; engagement in an agri-environmental scheme (AES). AES are voluntary five-year contracts between farmers and the government, where farmers receive CAP subsidies to implement specific environmentally-friendly practices on their farm. In dairy and beef cattle farming it can for example be a lower number of livestock units on the farm or reducing the use of fertilisers.

- Typology 1: Ecological farms are those farms that were *certified organic* farms in 2018 (47 farms), while non-ecological farms are those that were not certified (94 farms).
- Typology 2: Ecological farms are those farms that were *in conversion to organic farming* in 2018 (29 farms), while non-ecological farms were not (130 farms).
- Typology 3: Ecological farms are those farms that were *engaged in 2018 in an AES other than converting to organic farming* (33 farms), while non-ecological farms were not (126 farms).

- Typology 4: Ecological farms are those farms that declared in 2018 *using antibiotics only for treatment* (109), while non-ecological farms used antibiotics for treatment and for prevention (46 farms).
- Typology 5: Ecological farms are those farms that had *agroforestry* in 2018 (47 farms), while non-ecological farms had no agroforestry (32 farms).

3.13.4.2 Performance indicators

Three groups of indicators were computed: partial productivity indicators, profitability indicators, and market orientation indicator. As shown in Table 2, the partial productivity indicators consist in the average product of land (#1) and the average product of labour (#2). The profitability indicators compare revenue to cost. Revenue is either considered only from sales in private revenue-cost-ratios (indicators #3 and #4), or from sales as well as subsidies for public revenue-cost-ratio (indicators #5 to #6). The profitability indicators also differ in terms of the costs: either external labour and land only (#3 and #5), or external as well as own labour and land (#4 and #6). No other costs are included, due to poor quality data. The profitability indicators thus focus on labour and land costs. A final indicator proxies the market orientation (#7) and more precisely it describes how much a farm relies on public subsidies, compared to private revenues.

Table 2: Definition of the economic performance indicators computed

#	Indicator	Unit	Definition
	Partial productivity		
1	Average product of land	Euros per ha	Revenue from sales / UAA
2	Average product of labour	Euros per worked week	Revenue from sales / Number of total weeks worked on the farm
	Profitability		
3	Private revenue-cost-ratio not considering remuneration of owned production factors	unitless	Revenue from sales / (cost for paid labour + cost for paid rent)
4	Private revenue-cost-ratio considering remuneration of owned production factors	unitless	Revenue from sales / (cost for paid labour + cost for paid rent + imputed cost for own labour + imputed cost for own land)
5	Public revenue-cost-ratio not considering remuneration of owned production factors	unitless	Revenue from sales and subsidies/ (cost for paid labour + cost for paid rent)
6	Public revenue-cost-ratio considering remuneration of owned production factors	unitless	Revenue from sales and subsidies/ (cost for paid labour + cost for paid rent + imputed cost for own labour + imputed cost for own land)
	Market orientation		
7	Reliance on public subsidies	unitless	Revenue from sale / (Revenue from sales + subsidies)

3.13.5 Methods to compare economic performance between ecological and non-ecological farms

We use two methods to compare economic performance indicators presented above between ecological and conventional farms: comparison of means with t-tests and propensity score matching analysis.

The first straightforward method to compare groups of farms is to carry out t-tests of equality of means, to assess whether the means of the two groups of farms (ecological and non-ecological) are equal (for details, see Snedecor and Cochran, 1989). Specifically, for each performance indicator, we test the null hypothesis H0 that the mean of ecological farms is equal to the mean of conventional farms, against the alternative hypothesis H1 that the mean of ecological farms is different from the mean of conventional farms. A significant p-value would indicate a rejection of the null hypothesis, indicating that the means of the two groups are significantly different. Note that we use an adaptation of t-test, the Welch t-test, to accommodate situations where the variances of the two groups being compared are different (heteroscedasticity).

One potential problem when comparing farms with t-tests is that we do not compare similar farms. The group of ecological farms may be structurally different (e.g. smaller size, younger farmer) and in this case a significant difference in performance means may in fact be due to significant differences in farm structures. For this reason, we also use propensity score matching to compare performance between ecological farms and non-ecological farms (Rosenbaum and Rubin, 1983; Caliendo and Kopeinig, 2008; Stuart, 2010). Our objective is to assess the effect of treatment (i.e. the adoption of environmentally-friendly practices) on performance, specifically the average treatment effect on the treated (ATT). This statistic measures the change in performance when a farm became ecological, i.e. adopted environmentally-friendly practices.

Propensity score matching enables to construct a control group by matching each treated farm with a non-treated farm of similar characteristics. This is based on the probability to adopt environmentally-friendly practices, which is estimated on covariates that are selected as follows: (i) they influence the decision to adopt environmentally-friendly practices, (ii) but are not modified after adoption has taken place. An interesting discussion on covariate selection can be found in VanderWeele (2019). The covariates used to find similar farms in our analysis are: gender of the farmer (binary variable taking the value 1 if male, and 0 if female), education of the farmer (categorical variable with levels of primary school, middle school, agricultural high school, non-agricultural high school, agricultural university, non-agricultural university); age of the farmer (in years), experience of the farmer in farming (in years), UAA (in ha), share of owned land in UAA, regional dummies, dummy for localisation in LFA, and dummy for localisation in Natura 2000 area.

Once treated farms have been assigned a non-treated match, the effect of treatment on performance is measured with the ATT. On practical aspects, one can note that to estimate the treatment effect and its standard error, we fit a linear regression model with each of our performance indicators as the outcome, and the treatment and the covariates as additive predictors, and included the full matching weights in the estimation. Here the coefficient on the treatment is taken to be the ATT. Finally, a cluster-robust variance is implemented for the inference (see Abadie and Spiess, 2021).

3.13.6 Results

Results of the t-tests of equality of means between ecological farms and non-ecological farms (see table in the Appendix) consistently indicate that certified organic farms (ecological farms in Typology 1) and farms in conversion to organic farming (ecological farms in Typology 2) are significantly worse performer than non-ecological farms. This conclusion also holds when ecological farms are defined as farms engaged in AES other than organic conversion (Typology 3) but only in terms of output per hectare of land (indicator #1) and profitability ratios when subsidies are included as well as sales (indicators #5 and #6). In this typology 3, ecological and non-ecological farms are not significantly different in terms of output per labour (#2) and profitability ratios when only sales are considered in revenue (#3 and #4). We can also note that in the two other typologies (typology 4 regarding the use of antibiotics for treatment only, and typology 5 regarding agroforestry) ecological farms and non-ecological farms perform similarly on average, as the performance indicators are not significantly different. An exception relates to the market orientation: for each typology, ecological farms rely significantly more on subsidies since the ratio of sales to sales and subsidies (#7) is lower for ecological farms than for non-ecological farms (except for typology 5 about agroforestry where the difference is non-significant).

In summary, comparing ecological farms and non-ecological farms with t-tests of equality of means shows that (i) organic farms and farms engaged in AES (for organic conversion or not) are worse performing than other (non-ecological farms), (ii) limiting the use of antibiotics to treatment only or implementing agroforestry has no impact on economic performance, and (iii) ecological farms rely more on subsidies than non-ecological farms.

Moving to the results from propensity score matching (see Table A2 in the appendix), the conclusions are different. While certified organic farms (typology 1) and farms converting to organic farming (typology 2) were shown to be worse performing than non-ecological farms with t-tests (Table A1), the difference is non-significant when farms with similar structure are compared: the ATTs for all performance indicators are non-significant. This indicates that an organic (certified or in conversion) farm does not perform significantly more or less than a non-organic farm that is similar in terms of structure. In other words, on average farms that became organic (certified or in conversion) did not lose nor gain performance. The same conclusion holds for typology 4 where, on average, farms that adopted the practice of using antibiotics for treatment only (instead of treatment and prevention) did not lose nor gain performance.

The story is different for typologies 3 and 5. While some performance indicators did not change when a farm became ecological, some decreased significantly (shown by a negative and significant ATT). More precisely, when farms adopted AES (other than converting to organic), they experienced a decrease in output per hectare (#1) and per labour (#2), and in profitability accounting for external and own labour and land (#5 and #6). Similarly, when farms implemented agroforestry, they experienced a decrease in output per hectare (#1), and in profitability accounting for external and own labour and land when sales and subsidies are considered (#6).

3.13.7 Conclusion

We compare the economic performance of farms that apply a higher degree of environmentally-friendly practices (ecological farms) and farms with a lower implementation of such practices (non-ecological farms) for a sample of dairy and beef cattle specialist farms in France in 2018, whose data were collected through a specific survey. Using t-tests of equality of means and propensity score matching, seven economic performance indicators (related to partial productivities, profitability ratios and dependence on subsidies) were compared between ecological and non-ecological farms identified with five different typologies, depending on the practice considered.

Results show that t-tests of equality of means revealed a lower performance of organic (certified or in conversion) farms than other (non-ecological) farms, but the difference is not significant when propensity score matching is used. By contrast, while t-tests showed that implementing agroforestry had no impact on economic performance, propensity score matching revealed that it decreased output per hectare and profitability ratio (with revenue from sales and subsidies, and costs from external and own land and labour). This discrepancy in conclusion clearly shows the importance of taking into account the different structure (e.g. size, age) of ecological and non-ecological farms when comparing their performance.

As regard the two other typologies considered here, findings are consistent between t-tests of equality of means and propensity score matching: limiting the use of antibiotics to treatment only has no impact on economic performance, while engagement in AES (other than conversion to organic farming) decreases output per ha and profitability ratio when revenue includes sales and subsidies. The latter finding about AES is in line with the literature showing that implementing on farms practices requested from engagement in AES has a cost, and for this reason farmers receive AES subsidies to compensate for these costs. However, for our sample it seems that the compensation was not sufficient in 2018.

The main limit of this study is that variable costs (in particular costs of pesticides, fertilisers, concentrate feed, as well as veterinary costs) and fixed costs (e.g. depreciation) were not included in the profitability ratios due to low data quality. It can be expected that accounting for these costs may disadvantage non-ecological farms which rely more on these inputs than ecological farms, and may therefore change some conclusions. Further research could also focus on collecting robust data on environmental performance (nitrate pollution, biodiversity…) and social performance (labour force, working conditions, etc.…) in order to fully compare ecological and non-ecological farms

3.13.8 References

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3.13.9 Appendix

Table A1: Comparison of economic performance between ecological and non-ecological farms - Results of t-tests of equality of means

		Typology 1			Typology 2			Typology 3			Typology 4			Typology 5		
		Certified organic farming			Conversion to organic farming			Engagement in AES other than organic conversion			Antibiotics used for treatment only			Agroforestry		
		Ecol.	Non-ecol.	Sign.	Ecol.	Non-ecol.	Sign.	Ecol.	Non-ecol.	Sign.	Ecol.	Non-ecol.	Sign.	Ecol.	Non-ecol.	Sign.
1	Output per ha	1,565	2,731	***	1,501	2,774	***	1,787	2,552	***	2,240	2,878		1,518	1,828	
2	Output per labour unit	1,726	2,745	***	1,786	2,565	**	2,086	2,524		2,347	2,713		1,819	1,881	
3	Private revenue-cost-ratio not considering remuneration of owned production factors	6.57	10.78	**	4.85	11.57	***	10.39	10.22		9.64	12.82		6.48	5.56	
4	Private revenue-cost-ratio considering remuneration of owned production factors	7.44	13.07	***	5.83	13.83	***	12.64	12.66		11.89	15.6		8.6	6.94	
5	Public revenue-cost-ratio not considering remuneration of owned production factors	5.52	9.67	***	4.95	9.69	***	6.35	9.53	*	7.91	12.03		6.86	4.94	
6	Public revenue-cost-ratio considering remuneration of owned production factors	7.49	11.74	**	6.18	11.85	***	7.57	12.28	**	10.05	14.73		9.13	6.78	
7	Market orientation	0.71	0.83	***	0.72	0.83	*	0.72	0.85	***	0.80	0.88	**	0.69	0.79	

Notes: 'Ecol.' indicates the mean for the group of ecological farms. 'Non-ecol.' indicates the mean for the group of non-ecological farms. 'Sign.' indicates significance at 10% (*), 5% (**) and 1% (***) respectively for the t-test.

Table A2: Comparison of economic performance between ecological and non-ecological farms - Results of propensity score matching

		Typology 1		Typology 2		Typology 3		Typology 4		Typology 5	
		Certified organic farming		Conversion to organic farming		Engagement in AES other than organic conversion		Antibiotics used for treatment only		Agroforestry	
		ATT	Sign.	ATT	Sign.	ATT	Sign.	ATT	Sign.	ATT	Sign.
1	Output per ha	-43		99		-998	***	-55		-832	***
2	Output per labour unit	-34		304		-631	*	-229		-169	
3	Private revenue-cost-ratio not considering remuneration of owned production factors	-2.08		-2.89		0.51		-1.03		-3.87	
4	Private revenue-cost-ratio considering remuneration of owned production factors	-2.73		-1.85		1.69		-0.60		-4.08	
5	Public revenue-cost-ratio not considering remuneration of owned production factors	-0.50		0.48		-3.18	**	-1.67		-1.31	
6	Public revenue-cost-ratio considering remuneration of owned production factors	-1.13		1.21		-3.39	*	-2.03		-2.11	*
7	Market orientation	0.006		-0.01		-0.11	***	-0.05	**	-0.04	

Note 1: 'sign.' indicates significance at 10% (*), 5% (**) and 1% (***) respectively.

Note 2: the R-squared ranges from 0.1554 to 0.8269 depending on models and typologies.

3.14 Technical-economic performance of ecological farm types for matched cattle and sheep farms in Scotland (SRUC)

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3.14.1 Introduction and description of the case-study region

Scotland has just under 18,000 specialist cattle and sheep farms. Most of these farms are located in the west of the country, although there is a concentration of specialist cattle farms in the north east. In Scotland 88% of the agricultural land is classified as less favoured areas (LFA) (ScottishGovernment 2017) with 80% of cattle and sheep farms operating in a LFA (ScottishGovernment 2017). This has implications for the viability of these farms and the households that they support (Andrew P. Barnes, Thomson, and Ferreira 2020). The financial viability of beef but in particular sheep farms has been of concern for the last decade (Thomson 2011). The potential for Brexit-induced price reductions, especially the removal of income support measures are likely to see an accelerated decline in agricultural activity, land abandonment and moves away from agricultural livelihoods (Moxey and Thomson 2018). These trends have raised concerns in relation to biodiversity and the maintenance of traditional landscapes given 55% of Scotland's agricultural land is dedicated to upland sheep and mixed sheep and cattle farming (NatureScot 2020). The implications of these changes for landscapes and biodiversity vary from one sub region to another (Thomson 2011) but overgrazing is generally understood to be an issue (Ross et al. 2016). In terms of ecological farming practices on cattle farms, research suggests that there has been little change in the intensity of farming practices on cattle Scottish cattle farms over recent years (A. P. Barnes and Thomson 2014). One of the major concerns for cattle production are greenhouse gas emissions (GHG). A recent modelling study of Scottish beef finishing systems found that duration of finishing was negatively correlated to emissions but positively correlated to profitability (Kamilaris et al. 2020). This highlighted important trade-offs between profitability and GHG emissions that may need to be made.

3.14.2 Method

The LIFT farm typology is used to identify farms that conform with an ideal low-input, integrated or ecological type (Rega et al., 2021). The ecological category is defined as farms which are both low input and integrated. We present descriptive data on the number of farms in the low-input and / or high-integration categories with scores derived from analysis of the FADN sample. Since the number of low-input and / or high- integration farms in Scotland is limited relative to the EU level we recalculated quartiles based on the low-input and integrated scores and split our sample according to these quartiles quartiles. We used the bottom two quartiles and top two quartiles to create suitably sized groups for further analysis.

Differences in natural and socio-economic conditions are likely to affect all aspects of farm operation; this implies its classification as low-input and / or integrated as well as its efficiency. The underlying differences, between our farms can be considered selection bias. In order to reduce this we can identify a set of farms that are comparable with regard to their natural conditions, geographical region, access to inputs and production category (Hansen et al. 2021). In reducing these underlying differences we hope to be able to detect a truer effect of using a low-input or integrated technology on efficiency rather than the effect of other differences between our farms. In order to do this we conduct propensity score matching across our farm groupings. We used course exact matching implemented using the `MatchIt` package (Ho et al. 2011).

We used data envelopment analysis (DEA), which is a non-parametric method of calculating efficiency, to assess the technical-economic performance of farms in our sample. DEA does not assume the form of the production function or make assumptions about the probability distribution of the data (Cooper, Seiford, and Tone 2007). Each farm is benchmarked against the others by solving a series of linear programming problems and establishing an efficient frontier. One can assume (or not) that each farm is operating at an optimal scale; here we choose to assume that they are not so use variable returns to scale (VRS) and the operation only compares inefficient farms to efficient farms of a similar size. We also use a non-oriented model which assumes that farms are able to change inputs and outputs at the same time.

We used a slacks-based model (Tone 2001) which considers the sum of all slacks, beyond proportional reductions, within the efficiency score. This means it can provide a stronger discrimination between efficient and inefficient farms. Since it does not assume that all inputs or outputs must decrease proportionally it is arguably more applicable to real life situations than other DEA models, such as where inputs are substitutable (Tone 2015). The approach has been advocated for use in livestock systems by previous research (Soteriades et al. 2015). We implemented the analysis using the *deaR* package (Coll-Serrano et al. 2018).

We applied this model to our sample of cattle and sheep farms but also of subsets of the data by farm type and ecological type (low-input, integrated, and ecological). We therefore consider that these ecological types represent different production technologies in addition to being a cattle or sheep farm where similar management conditions apply. Due to low numbers of organic farms in the sample, we were not able to conduct a separate analysis for organic/non-organic farms.

We used a Wilcoxon test to see if there were significant differences between the average efficiency scores of farm categories or between other productivity indicators. We further conducted a secondary tobit regression to examine the effect or other variables on efficiency within the farm-type and subgroup samples.

3.14.3 Data

Data for this analysis came from the EU Farm Accountancy Data Network (FADN) for Scotland between 2011 and 2015. The FADN data provides accounting data for a sample of professional farms above a country specific size threshold from across the EU with a five-year rotating sampling system. We consider cattle and sheep farms for our analysis. These are defined by FADN as farms where at least 66% of their gross margin comes from cattle and sheep products respectively. In reality many of the farms in our Scottish sample are mixed cattle and sheep, but with an emphasis on one or the other. Our sample consists of 1006 observations of 245 distinct farms. This is made up of 630 cattle farm observations from 165 distinct farms and 376 sheep farm observations from 104 distinct farms. There are 24 where they were classified as sheep farms in one year but cattle in another or vice versa, emphasising the mixed livestock nature of some of the farms in our sample.

3.14.3.1 DEA data

As with the FADN WP1 typology, the data is pooled in order to generate a usable sample size for the case study. In order facilitate this any values in euros are deflated with appropriate indices with 2010 as the base year. The variable definitions and indices used can be found in Table 1.

Table 1: A table of variables used in the DEA

Variable	FADN Name	Units	Use	Description
Total output	SE131	EUR	Output	Sales and use of crop and livestock products and livestock plus changes in any product stocks / purchases of livestock.
Total assets minus land value	SE436 - ALNDAGR_CV	EUR	Input model	Fixed assets (valuation of land, farm buildings and forest capital, machinery and equipment and breeding livestock) and current assets (non-breeding livestock, stocks of agricultural products and other circulating capital)
Total intermediate consumption	SE275	EUR	Input model	Specific costs including inputs produced on the holding and overheads arising from production in the accounting year
Labour	SE011	Hours	Input model	Total number of hours worked on farm in year paid and unpaid
UAA	SE025	Hectares	Input model	Land area owend and/or rented by farm

We use total assets (minus land value), total intermediate consumption, labour (hours) and UAA (ha) as our inputs and total value of farm output as our output. We chose labour in hours rather than annual work units since they have a similar order of magnitude to our other variables. Since we investigate livestock farms we considered the fact that many farms in our sample also have common land. Ideally we would also like to include the number of grazing days on common land a farm has in a year per livestock unit, however not all farms have a common land value and to include this variable with would have to provide a dummy since 0 values for inputs cannot be used in DEA. Instead we include this variable in our matching criteria and in our secondary regression.

Prior to analysis the data was cleaned by checking for inconsistent and missing data. During this process 28 observations were removed due to incorrect livestock information or missing feed data. Since DEA is particularly sensitive to outliers we checked manually for outliers in the DEA variables using histograms and box plots. There were outliers from the perspective of individual variables at the top end of the sample, however considering multiple variables it appeared these were consistently linked to the same large farms. On this basis we did not have good reason to remove any further observations.

3.14.3.2 Propensity score matching data

Following Hansen et al. (2021) we account for four dimensions that might contribute to selection bias into one of the ecological groups. To account for difference in environmental conditions we include an indicator of whether or not the farm is classified as LFA. To account for geographical regions, we include NUTS2 region. To account for differences in access to inputs we include a variable for grazing days on common land. To account for production types, we include the number of livestock units.

3.14.3.3 Secondary regression data

The variables available to conduct secondary analysis are limited by the FADN. We include less favoured areas (LFA) status, organic status, percentage land rented, grazing days on common land, low input and integrated scores as well as their NUTS2 region.

3.14.4 Results

3.14.4.1 WP1 typology results

We analysed the results of the WP1 low-input classification on our sample we found that only 2 cattle farms and 7 sheep farms were classified as low input (score > 3) using the unweighted low-input score and 1 cattle and 14 sheep farms using the weighted scores. When we analysed the results of the WP1 integrated classification in our sample we found that 7 cattle farms and 67 sheep farms were classified as highly integrated. Using the weighted scores resulted we found 8 cattle farms and 79 sheep farms were classified as highly integrated.

These scores indicate that relative to other cattle farms in the FADN sample, Scottish cattle farms are high input since a large proportion of scores are between 1 and 2 and very few are above 3. While there are not many sheep farms with scores above 3 there a larger proportion have scores between 2 and 3 indicating that they are relatively low input. In terms of integration, Scottish cattle farms have a low degree of integration. We can see the bulk of the farms have scores between 1 and 2.5. Scottish sheep farms are more highly integrated, having a large proportion of the sample with scores above 2 and a proportion with scores above 3. Lastly there are only 34 organic sheep farms and 6 organic cattle farms in our sample.

3.14.4.2 WP1 typology adaptation

In order to elicit the differences in low-input and integrated farms within our Scottish sample we calculated the quartiles for the scores so that we have relatively even, usable groups for further analysis. We decided to proceed using only the weighted scores so all scores reported from here on refer to weighted scores. Using these cut off values we split our sample into four similarly sized groups. Since we are working with a small sample we collapsed the bottom and top two quantiles to give us a minimum of 295 in each sub sample of cattle farms and a minimum of 163 in each sub sample of sheep farms. We are also interested in identifying those farms in our sample that were both low input and highly integrated, suggesting that they might be considered as the most ecological. We have 207 cattle farms and 136 sheep farms in both the high-integration and low-input categories which we describe as the most ecological farms.

3.14.4.3 Propensity score matching

Propensity score matching enabled us to identify samples of high and low-input, high and low-integration and ecological and non-ecological farms that were more similar one another across key variables than in our original samples. This process reduces the sample size since some farms could not be matched within the defined bounds were removed.

3.14.4.4 Efficiency results with secondary regression

3.14.4.4.1 Results by farm type

We first ran an efficiency analysis on the full samples of cattle farms and sheep farms. The mean efficiency score for the cattle sample was 0.54 and the mean efficiency score for the sheep farm sample was 0.57.

Table 2 shows the results of our second stage regression for cattle and sheep farms. We see that for cattle farms now that other factors are included the low-input score in fact has a positive relationship with efficiency at the 0.05 level. Being situation in an LFA, or NUTS regions UKM5 or UMM6 compared to UKM2 also have a small positive but significant relationship at the 0.05 level with efficiency. The percentage of rented land has a small positive relationship with efficiency whereas the percentage of subsidies as a proportion of total revenue (sales + subsidies) has a negative relationship with efficiency. Need to consider livestock units.

Table 2: Regression results for cattle and sheep farms

	Cattle			Sheep		
	Estimate	Std. Error	p value	Estimate	Std. Error	p value
(Intercept):1	0.759	0.050	0.000	1.245	0.095	0.000
(Intercept):2	-1.972	0.037	0.000	-1.691	0.046	0.000
score_livestock_lu_weighted	0.110	0.024	0.000	0.125	0.044	0.004
score_livestock_integrated_weighted	-0.026	0.020	0.198	-0.190	0.038	0.000
LFA_YN	0.076	0.034	0.025	-0.118	0.077	0.126
NUTS2UKM3	0.025	0.036	0.492	-0.060	0.032	0.059
NUTS2UKM5	0.094	0.037	0.012	0.093	0.104	0.371
NUTS2UKM6	0.090	0.037	0.016	0.009	0.038	0.804
grazdays_score_grz_lu	-0.003	0.006	0.583	-0.005	0.010	0.643
lu_tot	-0.000	0.000	0.000	-0.000	0.000	0.251
debt_asset_ratio	0.053	0.061	0.388	-0.020	0.097	0.841
perc_uaa_rented	0.078	0.020	0.000	0.130	0.029	0.000
market_orientation_ratio	-1.589	0.102	0.000	-0.981	0.134	0.000
perc_paid_labour	0.009	0.043	0.824	-0.026	0.071	0.710
organicorganic	0.011	0.060	0.859	0.120	0.044	0.007

We see that for sheep farms both the low-input score and integrated scores have a relationship with efficiency score that is significant at the 0.05 level but they go in opposite directions with low-input scores having a positive relationship to efficiency, as on cattle farms and the integrated score a negative relationship. Being an organic farm also has a positive association with efficiency in this model. The location of sheep farms, nor their access to common land seem to make a difference to efficiency, which is surprising. However, the percentage of subsidies as a proportion of total revenue has a negative relationship with efficiency and perhaps accounts for much of area related inefficiency. We also see that the percentage of land rented has a positive relationship with efficiency as it did in the cattle sample.

3.14.4.4.2 Results by farm type and ecological type efficiency scores

Table 3 shows the results of our efficiency analysis by farm type and ecological category. A Wilcoxon test indicated a difference significant at the 0.05 level between the mean scores of high-integration compared to low-integration sheep farms. This stands in contrast to the comparison of scores in the unmatched samples where significant differences were detected between the mean scores of the high-input compared to low-input cattle farms, the most-ecological cattle farms compared to non-ecological cattle farms in addition to the high-integration compared to the low-integration sheep farms. This suggests that the matching process has removed some of the underlying heterogeneity which was in fact driving differences between the cattle farms in the unmatched analysis.

Table 3: Mean efficiency scores by farm type and ecological category

	Mean Efficiency	p value		Mean Efficiency	p value		Mean Efficiency	p value
low-input	0.591	0.321	high-integration	0.588	0.091	eco	0.604	0.973
high-input	0.599	-	low-integration	0.609	-	non-eco	0.599	-
low-input	0.632	0.246	high-integration	0.601	0.014	eco	0.628	0.596
high-input	0.659	-	low-integration	0.665	-	non-eco	0.645	-

3.14.4.4.3 Results by farm type and ecological additional productivity indicators

Table 4 shows the mean scores per indicator for a number of important productivity indicators for cattle farms. These are calculated using the matched samples.

Table 4: Productivity indicators for cattle farms by ecological type

Indicator	Low-Input Category	Mean	p value	Integrated Category	Mean	p value	Ecological Category	Mean	p value
equity_ratio	low	0.892	0.299	low	0.893	0.791	eco	0.903	0.057
equity_ratio	high	0.885	-	low	0.886	0.791	non-eco	0.881	-
market_orientation_ratio	low	0.321	0.000	low	0.322	0.000	eco	0.334	0.000
market_orientation_ratio	high	0.271	-	low	0.273	0.000	non-eco	0.278	-
output_per_capital_ratio	low	0.160	0.454	low	0.150	0.108	eco	0.153	0.165
output_per_capital_ratio	high	0.143	-	low	0.153	0.108	non-eco	0.150	-
output_per_intermed_ratio	low	1.103	0.214	low	1.109	0.212	eco	1.106	0.307
output_per_intermed_ratio	high	1.078	-	low	1.076	0.212	non-eco	1.084	-
output_per_labour_ratio	low	35.392	0.000	low	35.154	0.000	eco	32.935	0.000
output_per_labour_ratio	high	42.064	-	low	41.773	0.000	non-eco	41.651	-
output_per_land_ratio	low	850.910	0.000	low	782.775	0.000	eco	697.796	0.000
output_per_land_ratio	high	1,273.480	-	low	1,320.724	0.000	non-eco	1,232.244	-
private_rev_cost_ratioA	low	0.838	0.078	low	0.828	0.656	eco	0.836	0.255
private_rev_cost_ratioA	high	0.809	-	low	0.814	0.656	non-eco	0.814	-
private_rev_cost_ratioB	low	1.228	0.000	low	1.217	0.000	eco	1.251	0.000
private_rev_cost_ratioB	high	1.105	-	low	1.116	0.000	non-eco	1.122	-

Table 5 shows the mean scores per indicator for a number of important productivity indicators for sheep farms. These are calculated using the matched samples.

Table 5: Productivity indicators for cattle farms by ecological type

Indicator	Low-Input Category	Mean	p value	Integrated Category	Mean	p value	Ecological Category	Mean	p value
equity_ratio	low	0.897	0.074	low	0.904	0.003	eco	0.907	0.004
equity_ratio	high	0.849	-	low	0.850	0.003	non-eco	0.855	-
market_orientation_ratio	low	0.421	0.000	low	0.432	0.000	eco	0.439	0.000
market_orientation_ratio	high	0.331	-	low	0.332	0.000	non-eco	0.342	-
output_per_capital_ratio	low	0.155	0.038	low	0.148	0.013	eco	0.148	0.021
output_per_capital_ratio	high	0.179	-	low	0.186	0.013	non-eco	0.181	-
output_per_intermed_ratio	low	0.975	0.013	low	0.958	0.001	eco	0.964	0.014

Indicator	Low-Input Category	Mean	p value	Integrated Category	Mean	p value	Ecological Category	Mean	p value
output_per_intermed_ratio	high	1.049	-	low	1.055	0.001	non-eco	1.037	-
output_per_labour_ratio	low	26.327	0.000	low	25.906	0.000	eco	25.018	0.000
output_per_labour_ratio	high	35.394	-	low	34.303	0.000	non-eco	33.701	-
output_per_land_ratio	low	178.328	0.000	low	152.563	0.000	eco	140.520	0.000
output_per_land_ratio	high	518.229	-	low	510.309	0.000	non-eco	467.130	-
private_rev_cost_ratioA	low	0.704	0.002	low	0.684	0.000	eco	0.687	0.000
private_rev_cost_ratioA	high	0.775	-	low	0.789	0.000	non-eco	0.772	-
private_rev_cost_ratioB	low	1.216	0.003	low	1.205	0.216	eco	1.223	0.016
private_rev_cost_ratioB	high	1.153	-	low	1.177	0.216	non-eco	1.169	-

3.14.4.4.4 Low-input farm regressions

Table 6 shows the results for the secondary regression of cattle farms. For low-input cattle farms the only two variables that have a relationship with efficiency at the 0.05 level and a discernible effect size are the percentage of UAA rented and the percentage of subsidies as a proportion of total revenue. For high-input cattle farms being in UKM6 was associated with having a higher efficiency score compared to UKM2, we also see that the percentage of subsidies as a proportion of total revenue was significant, but the percentage of rented land was not. We should also note that we were not able to include organic as a variable in the high-input cattle model since none of the farms in this group were classified as organic and we were not able to include LFA as a variable in either the low or high-input sheep models because all sheep farms in these matched samples were in an LFA.

Table 6: Regression results for low-input and high-input cattle farms

	Low-Input Cattle			High-Input Cattle		
	Estimate	Std. Error	p value	Estimate	Std. Error	p value
(Intercept):1	1.011	0.173	0.000	0.733	0.111	0.000
(Intercept):2	-1.939	0.055	0.000	-1.869	0.054	0.000
score_livestock_lu_weighted	0.057	0.057	0.316	0.055	0.055	0.317
score_livestock_integrated_weighted	-0.051	0.033	0.125	0.008	0.034	0.811
LFA_YN	0.154	0.088	0.081	0.052	0.065	0.420
NUTS2UKM3	0.070	0.090	0.436	0.035	0.061	0.572
NUTS2UKM5	0.136	0.096	0.156	0.114	0.064	0.075
NUTS2UKM6	0.163	0.093	0.079	0.123	0.063	0.050
grazdays_score_grz_lu	0.017	0.010	0.102	-0.009	0.010	0.345
lu_tot	-0.001	0.000	0.000	0.000	0.000	0.382
debt_asset_ratio	0.024	0.091	0.788	0.102	0.116	0.378
perc_uaa_rented	0.105	0.030	0.000	0.065	0.037	0.082
market_orientation_ratio	-2.125	0.163	0.000	-1.480	0.164	0.000
perc_paid_labour	0.064	0.066	0.333	0.006	0.068	0.928
organicorganic	0.030	0.065	0.645	-	-	-

Table 7 show the results for sheep farms by low/high input type. For low-input sheep farms we found that low-input score had a positive relationship with efficiency whereas integration score had a negative relationship with efficiency. We also see that being in UKM3 was likely to result in a lower efficiency score relative to UKM2 (there were no low-input sheep farms in UKM5) as was a higher share of subsidies in total revenue and a higher percentage of paid labour. A higher percentage of rented UAA corresponded with a higher efficiency score as did being an organic farm.

Table 7: Regression results for low-input and high-input sheep farms

	Low-Input Sheep			High-Input Sheep		
	Estimate	Std. Error	p value	Estimate	Std. Error	p value
(Intercept):1	1.804	0.311	0.000	1.362	0.121	0.000
(Intercept):2	-1.713	0.071	0.000	-1.809	0.072	0.000
score_livestock_lu_weighted	0.326	0.095	0.001	0.026	0.072	0.723
score_livestock_integrated_weighted	-0.446	0.081	0.000	-0.201	0.051	0.000
NUTS2UKM3	-0.224	0.056	0.000	0.033	0.043	0.449
NUTS2UKM6	-0.073	0.058	0.211	0.151	0.058	0.009
grazdays_score_grz_lu	-0.019	0.018	0.288	0.006	0.015	0.682
lu_tot	-0.000	0.000	0.082	0.000	0.000	0.880
debt_asset_ratio	-0.328	0.215	0.126	-0.107	0.115	0.353
perc_uaa_rented	0.124	0.045	0.005	0.142	0.043	0.001
market_orientation_ratio	-1.024	0.196	0.000	-1.437	0.195	0.000
perc_paid_labour	-0.269	0.097	0.005	0.162	0.111	0.145
organicorganic	0.176	0.069	0.011	0.209	0.077	0.007

3.14.4.4.5 Integrated farm regressions

Table 8 shows the results for cattle and Table 9 shows the results for sheep where integrated score is included alongside other variables. Here we were not able to include LFA for high-integration cattle since all of this sample after matching were in a LFA. For the same reason we were not able to include organic as a variable for low-integration as none of these farms were organic.

Being in UKM6 relative to UKM2 was associated with a higher efficiency score for high-integration cattle but not low-integration cattle where being in UKM5 was associated with a positive relationship to efficiency. For low-integration cattle the percentage of rented land had a positive association with efficiency but no relationship was detected that was significant at the 0.05 level for high-integration cattle farms. Having a higher share of subsidies in total revenue was negatively associated with efficiency for high and low-integration cattle farms.

Table 8: Regression results for high and low integration cattle farms

	High Integration Cattle			Low Integration Cattle		
	Estimate	Std. Error	p value	Estimate	Std. Error	p value
(Intercept):1	1.119	0.202	0.000	0.667	0.118	0.000
(Intercept):2	-1.902	0.062	0.000	-1.846	0.051	0.000
score_livestock_lu_weighted	0.005	0.047	0.907	0.114	0.038	0.003
score_livestock_integrated_weighted	-0.042	0.059	0.476	-0.065	0.038	0.085
LFA_YN	-	-	-	0.100	0.087	0.253
NUTS2UKM3	0.186	0.126	0.140	0.019	0.058	0.739
NUTS2UKM5	0.184	0.128	0.152	0.179	0.062	0.004
NUTS2UKM6	0.277	0.125	0.027	0.106	0.060	0.078
grazdays_score_grz_lu	0.024	0.013	0.063	0.001	0.009	0.943
lu_tot	-0.000	0.000	0.021	0.000	0.000	0.782
debt_asset_ratio	0.226	0.152	0.137	0.033	0.088	0.708

	High Integration Cattle			Low Integration Cattle		
	Estimate	Std. Error	p value	Estimate	Std. Error	p value
perc_uaa_rented	0.061	0.039	0.114	0.102	0.031	0.001
market_orientation_ratio	-2.157	0.183	0.000	-1.382	0.157	0.000
perc_paid_labour	-0.015	0.088	0.862	0.072	0.063	0.252
organicorganic	0.070	0.086	0.418	-	-	-

Table 9: Results for high and low integration sheep farms

	High Integration Sheep			Low Integration Sheep		
	Estimate	Std. Error	p value	Estimate	Std. Error	p value
(Intercept):1	2.161	0.479	0.000	1.205	0.106	0.000
(Intercept):2	-1.572	0.082	0.000	-1.755	0.067	0.000
score_livestock_lu_weighted	0.223	0.094	0.017	0.201	0.057	0.000
score_livestock_integrated_weighted	-0.448	0.148	0.002	-0.278	0.053	0.000
NUTS2UKM3	-0.178	0.082	0.030	-0.036	0.043	0.399
NUTS2UKM6	-0.042	0.078	0.593	0.068	0.058	0.238
grazdays_score_grz_lu	-0.039	0.021	0.058	0.005	0.016	0.747
lu_tot	-0.000	0.000	0.444	-0.000	0.000	0.082
debt_asset_ratio	-0.236	0.266	0.374	-0.070	0.129	0.591
perc_uaa_rented	0.122	0.059	0.038	0.225	0.040	0.000
market_orientation_ratio	-1.320	0.246	0.000	-1.117	0.190	0.000
perc_paid_labour	-0.064	0.120	0.597	0.050	0.109	0.649
organicorganic	0.159	0.078	0.042	0.370	0.104	0.000

For sheep farms we see a positive relationship between the integration score and efficiency for both the low and high integration sample. In contrast we see a negative relationship between efficiency and the integration score. We see the same relationship between rented UAA and the percentage of subsidies in revenue here as we have previously with a positive relationship for share of rented land and negative for subsidies. Lastly, we see a positive relationship between being an organic farm and being more efficient.

3.14.4.4.6 Ecological farm regressions

Table 10 shows the results for cattle and Table 11 shows the regression results. We see that for ecological cattle farms only the percentage of rented UAA and percentage of subsidies in revenue have a significant relationship with efficiency score at the 0.05 level. In the non-ecological group we see a very weak positive relationship between efficiency and low-input score. We also see a positive effect of being in UKM5 or UKM6 relative to UKM2. We also see the same positive and negative relationships between percentage off UAA rented and percentage of subsidies in revenue as we did in the ecological group.

Table 10: Regression results for eco and non-eco cattle farms

	Eco Cattle			Non-Eco Cattle		
	Estimate	**Std. Error**	**p value**	**Estimate**	**Std. Error**	**p value**
(Intercept):1	1.207	0.239	0.000	0.784	0.083	0.000
(Intercept):2	-1.995	0.070	0.000	-1.836	0.047	0.000

	Eco Cattle			Non-Eco Cattle		
	Estimate	Std. Error	p value	Estimate	Std. Error	p value
score_livestock_lu_weighted	0.016	0.071	0.823	0.091	0.037	0.014
score_livestock_integrated_weighted	-0.058	0.058	0.321	-0.016	0.031	0.618
NUTS2UKM3	0.167	0.120	0.164	0.030	0.058	0.611
NUTS2UKM5	0.186	0.125	0.136	0.128	0.061	0.036
NUTS2UKM6	0.229	0.122	0.060	0.130	0.059	0.028
grazdays_score_grz_lu	0.017	0.014	0.229	-0.001	0.009	0.934
lu_tot	-0.001	0.000	0.000	0.000	0.000	0.644
debt_asset_ratio	0.150	0.167	0.370	0.079	0.083	0.342
perc_uaa_rented	0.089	0.042	0.034	0.069	0.029	0.018
market_orientation_ratio	-2.054	0.181	0.000	-1.563	0.149	0.000
perc_paid_labour	0.031	0.088	0.724	0.027	0.059	0.654
organicorganic	0.078	0.073	0.284	0.126	0.171	0.460

Table 91: Regression results for eco and non-eco sheep farms

	Eco Sheep			Non-Eco Sheep		
	Estimate	Std. Error	p value	Estimate	Std. Error	p value
(Intercept):1	1.983	0.556	0.000	1.160	0.112	0.000
(Intercept):2	-1.648	0.087	0.000	-1.689	0.064	0.000
score_livestock_lu_weighted	0.289	0.118	0.015	0.197	0.059	0.001
score_livestock_integrated_weighted	-0.502	0.148	0.001	-0.236	0.052	0.000
NUTS2UKM3	-0.243	0.080	0.002	-0.026	0.045	0.559
NUTS2UKM6	-0.054	0.078	0.493	0.064	0.059	0.277
grazdays_score_grz_lu	0.016	0.022	0.453	-0.006	0.016	0.725
lu_tot	-0.000	0.000	0.131	-0.000	0.000	0.154
debt_asset_ratio	-0.512	0.274	0.062	-0.097	0.131	0.460
perc_uaa_rented	0.040	0.062	0.516	0.236	0.041	0.000
market_orientation_ratio	-0.803	0.245	0.001	-1.210	0.193	0.000
perc_paid_labour	-0.209	0.121	0.083	0.045	0.106	0.667
organicorganic	0.251	0.083	0.002	0.295	0.094	0.002

For sheep farms we see a positive relationship between low-input score and efficiency and a negative relationship between integration score and efficiency in both the ecological and non-ecological groups. Being in UKM3 is negatively associated with efficiency relative to being in UKM2 (no farms in UKM5 were included in either of these samples) and this was significant at the 0.05 level for the ecological group. A higher percentage of rented land was associated with efficient which was significant at the 0.05 level for the non-ecological group. The percentage of subsidies in total revenue was negatively associated with efficiency in both groups as it has been in all of our results.

3.14.5 Discussion

We found that mean efficiency score for all of the sub samples was significantly higher than the mean efficiency score for the whole cattle and sheep farm samples but only between the high-integration and low-integration sheep farms did we find a significant difference between the mean efficiency scores of the matched samples. We could therefore argue that there was not a discernible difference in the technology used between low and high input cattle or sheep farms to warrant different models.

There is a stronger argument for different models based on the integration scores, particularly for sheep farms. The technology difference is arguably one of extensity of grazing and forage.

We found that for cattle farms, a higher low-input was positively and significantly associated with efficiency in the whole cattle sample and across all our sub groups except for the highly integrated group where no effect was detected. This makes sense since the low-input score was calculated on the basis of a weighted mean of inputs per livestock unit or hectare of land. It seems that farms which have a lower ratio of one sort of input to another also tend to have a lower ratio of inputs to outputs. No significant effect was detected for the integration score though the coefficient direction was always negative. Across sheep farms we detected a positive relationship between low-input score and efficiency in all but the high-input sheep group. We also found that there was a negative and significant relationship between efficiency and integration score in the whole sheep sample and across all of the sub groups. These findings are generally supportive of previous research on the relationship between efficiency and GHG emissions on Scottish dairy farms which found that farms which are more technically efficient and bigger or have higher yields are also more efficient in their emissions of GHGs (Shortall and Barnes 2013) and modelling of beef finishing systems (Kamilaris et al. 2020). While the low-input score does indicate the intensity of the operation and incorporates many categories of emissions (fuel, electricity, fertiliser and feed). The integration score on the other hand can be seen as a measure of extensity, identifying farms that have a higher proportion of forage in their diet and lower stocking density arguably contributing to ecosystem services (Battaglini et al. 2014).

The proportion of rented land is often included in studies on the adoption of farm management practices as well as efficiency (Baumgart-Getz, Prokopy, and Floress 2012)). The results are mixed with some finding that land is associated with lower efficiency in livestock farms (Latruffe * et al. 2004; Latruffe, Davidova, and Balcombe 2008) which follows the evidence found for adopting some environmental practices which is that where land is not owned investing in long-term changes to it is not desirable. On the other hand evidence has also been found for a positive relationship between rented land and efficiency (Latruffe et al. 2017) suggesting that the need to pay rent ensures the resource is more efficiently. Our findings provide some support to this latter view as we find a positive and significant relationship between rented land and efficiency across the majority of our models.

Previous research on dairy and other livestock farms has indicated that farms with a higher debt to asset ratio are likely to be less efficient (Davidova and Latruffe 2007; Ma, Renwick, and Zhou 2020) though not necessarily less productive or profitable (Ma, Renwick, and Zhou 2020). This provides some support agency theory: borrowers with higher debt incur higher costs which reduce the efficiency and profitability of the farm. We do not find any evidence to support this in our models.

A large proportion livestock farms in Scotland are situated in LFAs. Subsidies are available to these farms to compensate for farming on potentially less productive land, although the subsidies must be applied for. Some research has indicated that receiving these subsidies make no significant difference to farm efficiency (Baráth, Fertő, and Bojnec 2020). However, other evidence suggests that farms exposed to environmental constraints are less efficient (Manevska-Tasevska, Rabinowicz, and Surry 2016) so we use a binary indicator for LFA status and not just whether they receive a subsidy. We have not also included NUTS region as a variable since there is a significant overlap in these variables, for example all farms in UKM6 Highland and Island are in LFAs. Due to the high number of farms in LFA in our sample, after matching we were not always able to compare LFA status directly. In our full cattle and sheep samples we found that LFA has a significant positive associate with efficiency and no significant effect respectively.

Debates about the relationship of organic farming and efficiency are ongoing. Early evidence from Europe indicated that organic farms were less efficient, however evidence from the United States suggested that when self-selection into organic farming was controlled for, and organic technology is assumed to be distinct then there is little evidence that organic farms are less efficient than conventional farms (Mayen, Balagtas, and Alexander 2010). More recently organic farms in Norway have been found to be more revenue efficient than comparable farms at least when subsidies are counted in the output (Hansen, Haga, and Lindblad 2021). While ideally we would also calculate technical efficiency for organic farms as we have for low-input and integrated farms we instead include it here following (Manevska-Tasevska, Rabinowicz, and Surry 2016). As with LFA we were not able to include the indicator for organic farming in all of our sub models. However, we found a significant positive relationship between organic farming efficiency in our full sheep sample model but no detectable effect in our full cattle sample model and a positive significant relationship to efficiency where it was able to be included in the sub sample models.

Our strongest finding in the secondary regression was the significant negative relationship between subsidies as a proportion of total revenue across all of our modelled groups. It could be argued that subsidies should be taken into account in the efficiency analysis itself as a form of compensated efficiency (Manevska-Tasevska, Rabinowicz, and Surry 2016) since farmers consider how to generate revenue from subsidies as well as from the market. Others have included the ratio of subsidy to land (Latruffe et al. 2017) which also resulted in a negative relationship between a higher ratio and efficiency in the UK while there was a positive or no detectable effect in other countries.

The development of low-input livestock farms could be beneficial from an economic and narrow environmental perspective. Lower input farms appear to be more efficient and given their low-input nature are also likely to have lower GHG emissions. The benefits of the development of integrated livestock farms is less clear. More highly integrated farms were found to be less efficient. Organic farms were associated with high levels of efficiency even in the highly-integrated sample so at least relatively the organic price premium, or links to organic associations helped to improve efficiency. The environmental benefits of extensive farming systems are also strongly debated with trade-offs between the emissions intensity of the products they produce versus the generation of other positive ecosystem services which are often hard to quantify (Hodge 2000). For policy makers, providing support for integrated farming is difficult to justify on environmental grounds and for farmers it is not an appealing option in Scotland without support.

3.14.6 References

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4 Empirical analyses of technical-economic and environmental farm performance

4.1 Pesticide efficiency of French wheat producers under a stochastic frontier framework (INRAE)

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4.1.1 Introduction

In a recent article, Lechenet, et al. (2017), based on a sample of French crop farms, argue for a potential reduction in pesticide use between 37% and 60% depending on the type of pesticides (herbicide, fungicide, insecticide), and this without impeding farms profitability. The results of this article are seriously challenged by Frisvold (2019) in his extensive survey, which summarizes several decades of agricultural economic research related to the issues that must be considered when dealing with 'farmers' pesticides use decisions. It appears that in primal approaches considering pesticides as damage control inputs, many aspects matter, among which the specification of crop production functions and the treatment of the endogeneity of input levels in the estimation of these functions. If the literature related to the specification of crop production functions has flourished since the seminal article of Lichtenberg and Zilberman (1986), the endogeneity of pesticide levels has barely been addressed in the performance benchmarking literature. For instance, Karagiannis and Tzouvelekas (2012), using a stochastic frontier framework (SFA), decompose total factor productivity (TFP) using a damage control specification, ignoring the potential endogeneity of pesticides. Clearly, this omission might produce biased estimation results. Besides, in the SFA literature, applications have focused on output efficiency and not input-specific efficiency.

Our contribution in this article is to develop an input-specific efficiency measure using SFA, and to overcome the potential endogeneity issue by relying on a dual approach. Following the framework developed in Chambers and Lichtenberg (1994), we can derive pesticide demand and then adjust this function to account for inefficiency. The obtained model is estimated, using a maximum likelihood approach, on a large sample of about 2,000 French wheat producers over the period 1998 to 2014. Our results reveal a potential reduction of pesticides by about 15%, which is much lower than the figures reported in the study by Lechenet, et al. (2017). We also find crop diversification to positively impact damage abatement only for low levels of pesticide use.

4.1.2 Description of the case study region

As shown in Figure 1, the farms we consider in this study are located in the northeast of France. Most of them (83%) belong to *département*[19] of Marne, the other farms being located in adjacent *départements*, namely Aisne (02), Ardennes (08), Aude (10), Haute-Marne (52) and Seine-et-Marne (77).

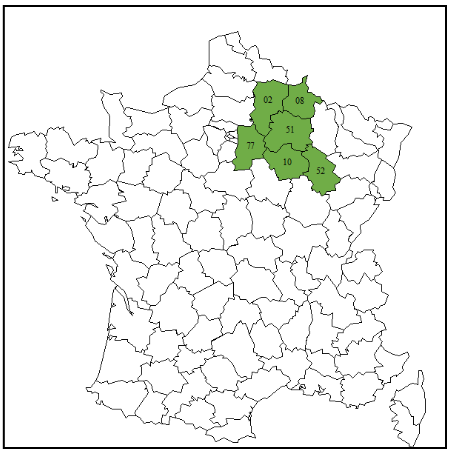

Figure 1: Case study area

This region, located in part in chalky champagne, is characterised by silty soils and calcareous soils, both of which have good agronomic properties. This makes it a very productive region for crops and allows farms to have relatively diversified cropping systems. Therefore, if cereals and oilseeds, wheat especially, are the main crops in the area and account for a substantial share of farm acreages, many farms (about 89% in our sample) also produce sugar beet a very profitable crop, as well as potatoes. Alfalfa is also cultivated in the region because of the presence of a downstream (dehydration) industry.

Therefore, our case study area farms are essentially large specialised crop farms with relatively intensive production practices allowing them to achieve the high potential yields offered by the soil conditions of the region.

4.1.3 Method

We develop an input-specific efficiency measure using a stochastic frontier analysis (SFA) approach to evaluate crop farmers' (in)efficiency in their uses of pesticides. To overcome potential issues related to the endogeneity of inputs levels in the estimation of production functions (see Frisvold, (2019) for an extensive survey of the problems that must be considered when dealing with farmers' pesticides use decisions), we rely on a dual approach. We start from a production function, where pesticides are represented as damage control input and assume profit maximisation behaviour. Following the framework developed in Chambers and Lichtenberg (1994), we derive a pesticides demand function and adapt this function to account for inefficiency. The obtained model is then estimated using a maximum likelihood approach.

4.1.3.1 Theoretical framework

We start with a crop production function defined as

$$y_{it} = g_{it} f(\mathbf{x}_{it}) \tag{1}$$

[19] A *département* is a French territorial division.

where y_{it} is the yield of the considered crop for farmer i in year t , $\mathbf{x}_{it}$ is a vector of productive inputs and g_{it} is the level of damage abatement provided by a single damage control input z_{it} (pesticides in our case study).

In the presence of inefficiency in pesticides use, we can formulate the damage control function as

$$g_{it} \leq G(z_{it}) \tag{2}$$

For computation purpose, we use an additive parametrisation of the inefficiency as follows:

$$\begin{gathered} g_{it} = G(z_{it} - \eta_{it}) \\ \eta_{it} \geq 0 \end{gathered} \tag{3}$$

In (3) $\eta_{it} \geq 0$ is the damage-control-input-oriented technical inefficiency, and it captures the volume of pesticides that is overused in producing the damage abatement level $g = g_{it}$. In other words, even if a producer uses a level z_{it} of pesticides, it is worth $z_{it} - \eta_{it}$. An implicit assumption of our formalisation is that the abatement function g_{it} is increasing in z_{it}. Moreover, following the damage control literature, the level of damage abatement (g_{it}) is defined such that $g_{it} \in (0,1)$ (Babcock, et al., 1992; Carrasco-Tauber and Moffitt, 1992; Lichtenberg and Zilberman, 1986).

Now, let us assume a profit-maximising producer:

$$\begin{gathered} \pi(p_{it}, \mathbf{w}_{it}, v_{it}) = \max_{y,x,z} p_{it} y_{it} - \mathbf{w}_{it}{}' \mathbf{x}_{it} - v_{it} z_{it} \\ s.t. \quad y_{it} = G(z_{it} - \eta_{it}) f(\mathbf{x}_{it}) \end{gathered} \tag{4}$$

As underlined in Chambers and Lichtenberg (1994), in a dual representation of pesticide technology, the first step is to characterize the cost of the abatement function, which can be defined as

$$c(v_{it}, g_{it}) = \min_{z} v_{it} z_{it} \quad s.t. G(z_{it} - \eta_{it}) = g_{it} \tag{5}$$

$c(v, g)$ possesses the properties of a traditional cost function.

Going back to (4), the profit maximisation program can equivalently be transformed as:

$$\begin{gathered} \pi(p_{it}, \mathbf{w}_{it}, v_{it}) = \max_{\mathbf{x},z} \{p_{it} G(z_{it} - \eta_{it}) f(\mathbf{x}_{it}) - \mathbf{w}_{it}{}' \mathbf{x}_{it} - v_{it} z_{it}\} \\ \pi(p_{it}, \mathbf{w}_{it}, v_{it}) = \max_{x,g} \left\{p_{it}\, g_{it} f(\mathbf{x}_{it}) - \mathbf{w}_{it}{}' \mathbf{x}_{it} - \left[\min_{z} v_{it} z_{it} : G(z_{it} - \eta_{it}) \geq g_{it}\right]\right\} \\ \pi(p_{it}, \mathbf{w}_{it}, v_{it}) = \max_{\mathbf{x},g} \{p_{it}\, g_{it} f(\mathbf{x}_{it}) - \mathbf{w}_{it}{}' \mathbf{x}_{it} - c(v_{it}, g_{it})\} \\ \pi(p_{it}, \mathbf{w}_{it}, v_{it}) = \max_{g} \left\{\max_{\mathbf{x}} [p_{it}\, g_{it} f(\mathbf{x}_{it}) - \mathbf{w}_{it}{}' \mathbf{x}_{it}] - c(v_{it}, g_{it})\right\} \\ \pi(p_{it}, \mathbf{w}_{it}, v_{it}) = \max_{g} \{R(p_{it}, \mathbf{w}_{it}, g_{it}) - c(v_{it}, g_{it})\} \end{gathered} \tag{6}$$

Where $R(p_{it}, \mathbf{w}_{it}, g_{it})$ is a restricted short-run profit function (Chambers and Lichtenberg, 1994). Solving the last line of (8) yields

$$R_g(p_{it}, \mathbf{w}_{it}, g_{it}) = c_g(v_{it}, g_{it}) \tag{7}$$

where R_g and c_g respectively denote the first order derivative of R and c with respect to g. This implies that the optimal level of abatement, g_{it}, is a function of input and output prices: $g_{it} = g(p_{it}, \mathbf{w}_{it}, v_{it})$.

4.1.3.2 Econometric specification

As pointed out in Chambers and Lichtenberg (1994), observations on g are unavailable and one has to specify a parametric representation for $G(z_{it} - \eta_{it})$. The identification strategy we adopt here proceeds as follows.

First, we define a specification for $G(z - \eta)$. Following Lichtenberg and Zilberman (1986), we consider the exponential and the logistic specifications, where a diversification index (T_{it}) is introduced as a factor affecting the damage control function.

In the case of the exponential specification, we have

$$G(z_{it} - \eta_{it}, T_{it}) = 1 - \exp[\alpha_t - \lambda(z_{it} - \eta_{it}) + b_1\, T_{it} + b_2\, T_{it}(z_{it} - \eta_{it})] \tag{8}$$

and in the case of the logistic specification, the abatement function takes the form:

$$G(z_{it} - \eta_{it}, T_{it}) = \frac{1}{1 + \exp[\theta_t - \gamma(z_{it} - \eta_{it}) + c_1 T_{it} + c_2 T_{it}(z_{it} - \eta_{it})]} \tag{9}$$

The α and θ parameters are assumed to vary from year to year to capture yearly exogenous factors like climate and weather events that may have an impact on crop damages.

Solving for the level of pesticides yields

$$z_{it} = \frac{\alpha_t + b_1 T_{it} + \ln[p_{it} y_{it}(\lambda - b_2 T_{it}) + \ v_{it}] - \ln\ v_{it}}{\lambda - b_2 T_{it}} + \eta_{it} \tag{10}$$

for the exponential specification, and

$$z_{it} = \frac{\theta_t + c_1 T_{it} + \ln[p_{it} y_{it}(\gamma - c_2 T_{it}) - \ v_{it}] - \ln\ v_{it}}{\gamma - c_2 T_{it}} + \eta_{it} \tag{11}$$

in the case of the logistic specification.

In both (10) and (11) pesticide demand equations, $p_{it} y_{it} = R_{it}$ is the revenue associated with the production of output y_{it}. To overcome potential endogeneity issues related to the existence of unobserved factors affecting both the use of input z_{it} and the production of output y_{it}, R can be approximated, using a flexible functional form which is a function of production inputs and output prices. In our case, we choose the Translog specification to make sure that the prediction of R is always positive.

Equations (10) and (11) are estimated as:

$$\begin{aligned} z_{it} &= \frac{\alpha_t + b_1 T_{it} + \ln\left[\widehat{R_{it}}(\lambda - b_2 T_{it}) + \ v_{it}\right] - \ln\ v_{it}}{\lambda - b_2 T_{it}} + \eta_{it} + \omega_{it} \\ z_{it} &= \frac{\theta_t + c_1 T_{it} + \ln\left[\widehat{R_{it}}(\gamma - c_2 T_{it}) - \ v_{it}\right] - \ln\ v_{it}}{\gamma - c_2 T_{it}} + \eta_{it} + \omega_{it} \end{aligned} \tag{12}$$

Where ω is the noise (two-sided) component $\left(\omega \sim \mathcal{N}(0, \sigma_\omega^2 = \exp(W_\omega))\right)$. We assume that η follows a half-normal distribution $\left(\eta \sim \mathcal{N}^+\left(0, \sigma_\eta^2 = \exp\left(W_\eta\right)\right)\right)$.

An advantage of deriving the demand for pesticides as in (12) is to prevent endogeneity issues that mainly affect the production technology's primal representation. Here the demand for pesticides only depends on its price, an approximation of the revenue and the entropy level T.

Equations in (12) can be estimated using a maximum likelihood approach by writing the convolution of $\eta + \omega$ (Aigner, et al., 1977). To account for drivers of pesticides inefficiency, σ_η^2 is reparameterised as $\sigma_\eta^2 = \exp(\boldsymbol{q}'\boldsymbol{\delta})$ where $\boldsymbol{q}$ is a vector of inefficiency determinants (Caudill and Ford, 1993, Caudill, et al., 1995, Reifschneider and Stevenson, 1991).

4.1.4 Data

Our model is estimated on an unbalanced panel data set containing 10,263 observations of 1,765 wheat producers located in our case study area over the period 1998 to 2014. This sample has been extracted from data provided by an accounting agency situated in the Marne *département*. It contains detailed information about crop production for each farm (acreages, yields, input uses, and crop prices at the farm gate). These data report input expenditures per crop at the farm level. The corresponding input quantities are computed by using the fertiliser, pesticide, and seed price indices issued by the French Department of Agriculture at the country level. Finally, each farm's number of different crops grown each year is used as a crop diversification index (*T*).

Our empirical application focuses on wheat, which is the main crop produced in the area. Wheat acreage represents one-third of the total agricultural area in our sample.

Descriptive statistics of the data are presented in Table 1.

Table 1: Descriptive statistics of the data

Variable	**Mean**	**Standard deviation**	**Coefficient of variation**
Wheat revenue (Euros/ha) - R_{it}	1,125	334.33	0.30
Wheat yield (ton/ha) - y_{it}	8.76	1.03	0.12
Wheat price (Euros/ton) - p_{it}	129.13	37.95	0.29
Pesticides price index – v_{it}	101.72	3.83	0.04
Pesticides quantity index (per ha) - z_{it}	1.57	0.35	0.23
Diversification index - T_{it}	6.18	1.28	0.21
Total Utilised Agricultural Area - UAA (ha)	183.25	95.29	0.32
Wheat acreage (ha)	58.16	34.76	0.60
Capital K (Euros/ha)	1,435	886	0.61
Nitrogen quantity index (per ha)	1.88	0.42	0.22
Seeds quantity index (per ha)	0.68	0.27	0.40
Number of producers	1,765		

As shown by the figures in Table 1, the farms in our sample are rather large, highly productive, with wheat yields close to 9 tons per hectare, and have relatively diversified acreages since they grow 6 crops each year on average. These are typical characteristics of specialised crop farms in this geographical area.

4.1.5 Results

The maximum likelihood estimates are presented in Table 2.

The results obtained with the exponential and logistic specifications are virtually very similar, which shows their robustness. In both cases, parameters are significantly estimated and generally have expected signs.

Interestingly, parameter b_1 is positive and parameter b_2 is negative, implying that crop diversification has a positive impact on damage abatement if no pesticides are used but this impact decreases with an increase in the volume of pesticides used. This is further illustrated on Figure 4.

The average efficiency of pesticide use is about 82%. As shown in Figure 2, efficiency scores range from 65% to 95%. Larger farms, in terms of UAA and capital, are more efficient.

Pesticides could be reduced by 5% to 35% without impacting wheat yield if all farmers were fully efficient in using pesticides. These figures are much lower than those found by Lechenet et al. (2017) who did not account for endogeneity issues in the estimation of production function and found some cases where pesticides had a negative impact on yields.

The average abatement level is equal to 92.88% and could reach 94.84% if farmers were fully efficient.

Table 2: Estimation results of models

Variables	Damage abatement specification	
	Exponential specification	Logistic specification
Pesticides demand function		
λ / γ	1.86***	1.97***
b_1 / c_1	-0.036***	-0.028**
b_2 / c_2	0.089***	0.079***
α / θ	-0.492***	-0.263***
Inefficiency determinants		
Intercept	0.415	0.431
$\log(UAA)$	-0.165***	-0.166***
$\log(K)$	-0.224***	-0.225***
Noise component		
W_ω	-2.875***	-2.876***
Log-likelihood	-2922.884	-2919.363
Average efficiency (%)	82.33	84.60
Average abatement g (%) without inefficiency	94.84	95.20
Average abatement g (%) with inefficiency	92.88	93.56
Number of observations	10,263	10,263

Note: The model is estimated with year dummies to account for the α_t and θ_t parameters in equations in (18).

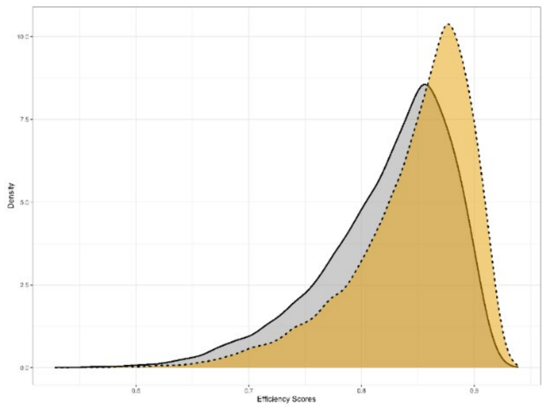

Figure 2: Efficiency scores distribution

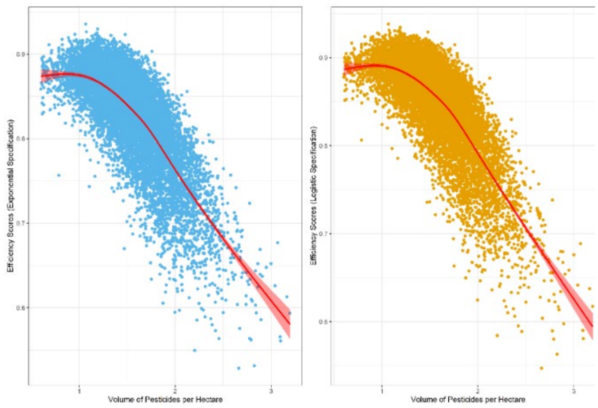

Figure 3: Efficiency scores and pesticide use

Figure 3 shows that efficiency decreases with the volume of pesticides used per hectare. These results may imply some scale effects associated with the efficient use of pesticides.

Figure 4 represents the evolution of damage abatement with the quantity of pesticides simulated with our models for the different numbers of crops grown by farmers in our sample, which range from 1 to 10. As expected, the damage abatement is an increasing function of the quantity of pesticide. More interestingly, we can distinguish 3 parts in these graphs. For very low levels of pesticides the number of crops positively impacts damage abatement. This could reflect low-input crop (ecological) crop production practices where farmers take advantage of crop diversification to manage pests. For medium levels of pesticides, the number of crops has a negative impact on damage abatement. This might correspond to the common case of relatively intensive crop production practices. For very high levels of pesticides, the number of crops has no impact on damage abatement. At these high levels corresponding to very intensive crop production practices, pesticides eliminate almost all the pests since the damage abatement function asymptotically converges to one.

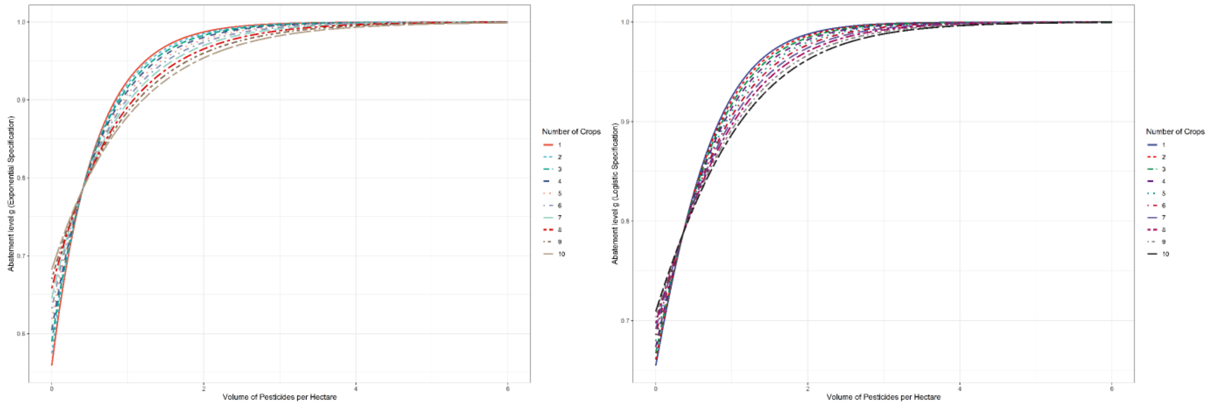

Figure 4: Average evolution of g depending on pesticides volumes and crop diversification

Figure 5 exhibits the relation between pesticide demand and its price while accounting for crop diversification. In the figure one can see an apparent decrease in pesticide demand with the price. On the other hand, a disparity appears depending on the level of crop diversification. For instance, when the price of pesticide is low, farmers use a lot of pesticides and do not take advantage of crop diversification to manage pests (on the contrary, growing more crop may incite them to use more pesticides to save time in managing pests), while when pesticide price increases they take more advantage of crop diversification. A tax on pesticide could thus incite farmers to manage their acreages so as to better exploit crop diversification to reduce their use of pesticides.

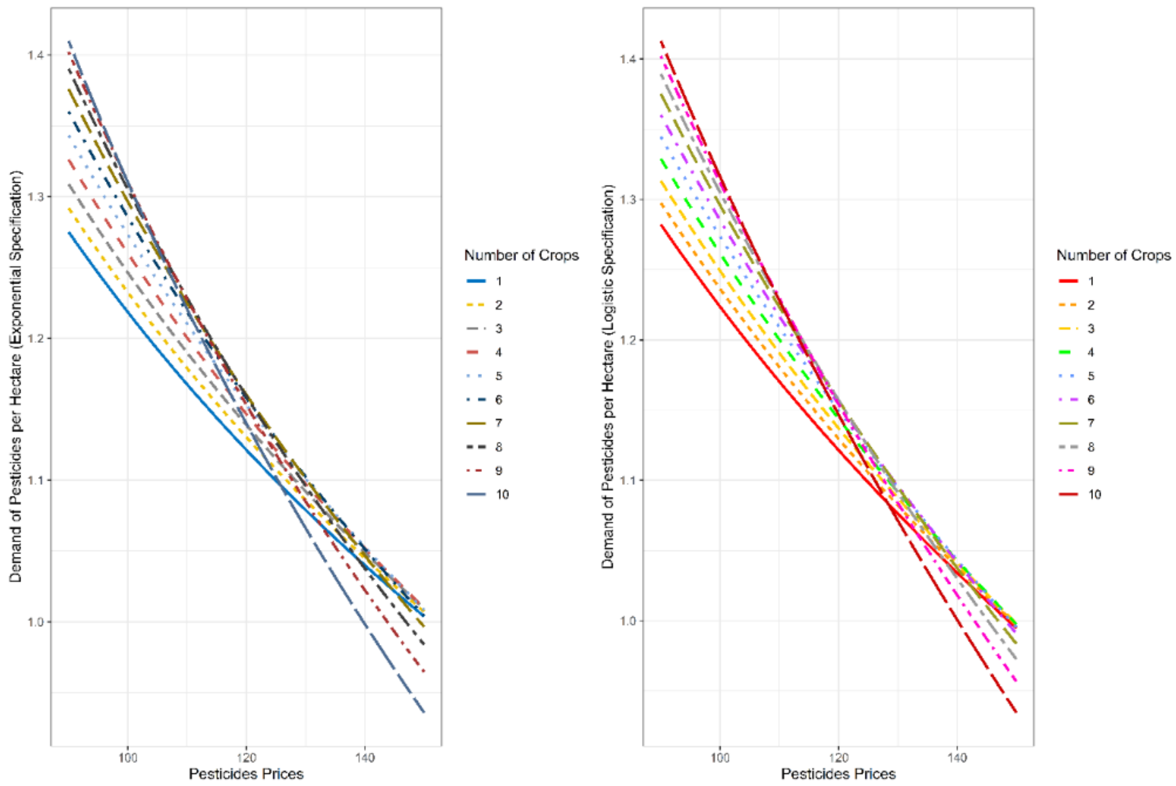

Figure 5: Evolution of pesticides demand depending on prices and number of crops

4.1.6 Discussion and conclusion

This work focuses on re-assessing farmers' potential inefficiency in the use of pesticides. To this aim, pesticides are treated not as productive inputs but as a damage control input. Under this assumption coupled with a profit-maximising behaviour, we derive pesticide demand which is a function of the revenue, crop diversification, and inefficiency. Our application to a sample of French wheat producers which exhibit a level of inefficiency ranging between 5% and 35%. On average, farmers could reduce by almost 15% their consumption of pesticides per hectare without affecting their yield. Moreover, our results show that crop diversification matters only for a very low level of pesticide use and has a null influence on damage abatement at high levels of pesticides.

Two types of recommendations for pesticide reduction policies can be drawn from these results. First, contrary to the findings of Lechenet et al. (2017), our results on efficiency show that the reductions in pesticide use that could be achieved through only a more efficient use of pesticides by farmers, and thus without a decrease in their productivity, are small. Thus, a public intervention seems necessary to encourage farmers to reduce their pesticide use, either by compensating them for the loss of profit due to the decrease in their productivity or by making pesticides more costly through a taxation policy. Second, our results on the effects of crop diversification on damage abatement suggest that, if a public policy was implemented to discourage the use of high dosages of pesticides, farmers could fully benefit from the positive impacts of crop diversification, which would, in turn, limit their loss of productivity, and thus profit.

4.1.7 References

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4.2 Technical-economic and environmental farm performance of dairy farms in Austrian case study regions Steyr-Kirchdorf and Salzburg und Umgebung (BOKU)

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4.2.1 Introduction

The aim of the present study is to investigate and compare farm performance of a broader variety of ecological dairy farming systems in two Austrian case study regions. Austria is a particularly interesting case for such an analysis, as the dairy sector has already undergone an ecological transition, which the EU currently strives to achieve at a broader scale. Based on data from the LIFT large-scale farmer survey (Tzouramani et al., 2019), we calculate several indicators of technical-economic farm performance, comprising profitability indicators including/excluding subsidies and opportunity costs for own production factors, partial productivity indicators and finally efficiency measures estimated with data envelopment analysis (DEA). In order to also reflect non-marketable outputs of ecological farming systems, we additionally investigate performance indicators related to environmental performance and animal welfare. All indicators are compared according to the degree of ecological approaches adopted by farms in the case study region. Further, drivers of farm performance are assessed with second-stage regression analyses.

4.2.2 Description of case study region

The Austrian case study region consists of the two NUTS3 regions Steyr-Kirchdorf (AT314) and Salzburg und Umgebung (AT323). Both regions are situated at the northern edge of the Alps and northern alpine foothills. They cover a broad gradient of site conditions, ranging from very fertile and intensively used arable land and grassland at lower elevations in the north to more marginal grassland in the mountainous south. Both regions are consequently characterised by a large share of farms specialised in grazing livestock and dairy farming, which make up 10% of all farms with milk delivery in Austria. In general, dairy farms in Austria are mostly family farms with roughly 33 ha utilised agricultural area (UAA), 22 dairy cows and 36 total livestock units on average (LBG, 2020). Dairy farms in the case study region have a similar structure.

When looking at the degree of ecological approaches adopted by dairy farms in Austria and the case study region in particular, two main production systems are most common: organic farming and silage-free milk production. The share of organic farms in Austria is with a total of 18% quite high compared to the average of the European Union. This is also true, when looking at farms with milk delivery to dairies, where the percentage of organic farms is with roughly 25% even higher. While Steyr-Kirchdorf reflects these values quite well, the share of organic farms and organic farms with milk delivery compared to all farms with milk delivery is even higher in Salzburg und Umgebung with 43% and roughly 52%, respectively. Especially in Salzburg und Umgebung silage-free milk production plays an important role for dairy farms, which is important for the production of hard cheese. This practice is also certified within the EU quality scheme as traditional speciality guaranteed (TSG)[20] under the name haymilk and many farms, producing silage-free milk are certified as haymilk TSG farms. Production of haymilk TSG limits feed for cattle to fresh forage and hay, complemented to a limited degree by grain. Additionally, no fermented fodder (silage) and genetically modified feed is allowed. Production of haymilk TSG can be applied on conventional as well as organic farms, whereas the combination with organic farming is especially common in Salzburg und Umgebung (Strauss and Darnhofer, 2015). From an environmental point of view, haymilk is also associated with a less intensive usage of grassland, as grass can be cut less often, when hay is produced, compared to silage, which can be beneficial for biodiversity on grassland. Also, as for organic and organic haymilk farms, concentrate feed costs are higher, these farms tend to use less external feed, resulting in a higher degree of circularity of feed input (i.e. more feed comes from the farm). In the context of the LIFT project conventional haymilk and organic haymilk systems thus share some similarities with low-input and integrated farming systems, as defined in LIFT Deliverables 1.1, 1.3 and D1.4 (Rega et al., 2018; Rega et al., 2019; Rega et al., 2021), additionally to the characteristics of organic farming systems, also described in these Deliverables.

4.2.3 Method

We use the farming systems described in the previous section to differentiate farms according to an increasing degree of ecological approaches adopted. Specifically, we differentiate between (i) conventional farms as the most intensive and from an environmental point of view unrestricted production system, followed by (ii) conventional haymilk farms, complying with the standards of haymilk TSG, (iii) organic farms, which comply with the standards of organic farming and (iv) organic haymilk farms, combining the standards of haymilk TSG and organic farming, which we consider as the most extensive and ecological farming system.

In order to investigate technical-economic and environmental performance of these four groups, we use several indicators. In terms of technical-economic performance we particularly calculate profitability indicators, partial productivity indicators and efficiency indicators. For environmental performance we calculate several simple indicators, an aggregated animal welfare index (AWI) and also efficiency indicators.

Profitability indicators are calculated as revenue cost ratio (RCR). The advantage of using ratios is that they are easy to interpret and compare. A ratio greater than one means that a farm is profitable, while a ratio smaller than one indicates the opposite. Similar indicators have been also used in the literature (Davidova et al., 2002; Bojnec and Latruffe, 2013). We calculate these RCRs with and without considering public payments to farms and with and without opportunity costs of the three production factors land, labour and capital in order to be able to compare farms depending on structural differences in terms of ownership of the production factors (e.g. a farm, operating mainly on rented land vs. a farm operating mainly on own land). For the calculation of opportunity costs of production factors we use farm-specific rental prices, which are weighted according to the share of arable land and grassland to evaluate land. In order to evaluate labour, we use a uniform wage of 15 EUR/hour, which is derived from average costs for outsourcing work to a machinery ring. For capital we use a uniform interest rate of 1%. This results in a total of 4 RCRs.

With respect to productivity, we compute quantitative partial productivity indicators, by dividing output through the individual inputs. In order to assess overall productivity of farms, we also calculate efficiency indicators, which consider all inputs and outputs jointly and additionally express productivity

[20] https://ec.europa.eu/info/food-farming-fisheries/food-safety-and-quality/certification/quality-labels/quality-schemes-explained_en

of farms as a relative measure, in comparison to benchmark farm(s). The two most common approaches to estimate efficiency are stochastic frontier analysis (SFA) and data envelopment analysis (DEA) (Coelli et al., 2005). In this analysis we rely on (DEA) to estimate efficiency indicators. DEA is a non-parametric method and has been used for a long time to analyse technical-economic farm performance of dairy farms (Fraser and Cordina, 1999). When implementing a DEA model, the question arises, whether to measure efficiency based on an input- or output orientation. We consider an output oriented DEA model, which is quite common in agriculture, as farmers have more control over their input use, meaning they try to maximise their output, based on their chosen input level (Karagiannis, 2014). Bias corrected efficiencies, which consider the truncated nature of DEA efficiencies, were calculated with R (R Development Core Team, 2021) and the package {rDEA} (Simm and Besstremyannaya, 2020).

In order to compare, whether technical-economic and ecological farm performance of at least one group differs statistically significant compared to all others, we use a non-parametric Kruskal-Wallis rank sum test and additionally compare each group with one another individually using a non-parametric Mann-Whitney-U test. Finally, we assess the effect of drivers on efficiency indicators with a second-stage truncated regression with the double bootstrap approach from Simar and Wilson (2007).

4.2.4 Data

The collected data for this analysis is based on the LIFT large-scale farmer survey (Tzouramani et al., 2019) and refers to the year 2018. In our case study region, the survey was conducted face to face by BOKU staff between December 2019 and March 2020. Respondents were recruited with support of the regional chambers of agriculture, which provided contacts to farms. Additional respondents were identified via snowball sampling. The main aim in the sampling process was to cover a broad degree of ecological farm types in the survey.

In total we calculate four different DEA models, all with identical input definitions, but different output definitions. The definitions of in- and outputs are provided in Table 1. As inputs we use land, labour, capital, intermediate expenses and herd size, with similar input specifications being quite common for dairy farms (Kellermann and Salhofer, 2014). Land is measured in ha UAA. Labour is measured in annual working units (AWU) according to the definition of the Austrian FADN data, where a value of one denotes full-time equivalent employment of one person and includes unpaid family labour as well as hired labour. Intermediate expenses are expressed in Euros and include regular expenses for e.g. feed, energy, plant protection or machinery services, among others. Herd size is measured in livestock units (LSU), according to FADN definitions. For capital, depreciated recreation/replacement values of main buildings and machinery were calculated based on a detailed assessment of type, size and age and then summed up to arrive at an estimate for capital stock.

While outputs in model 1 (total output excluding subsidies) and model 2 (milk in kg, other output in EUR) focus on technical economic farm performance, outputs in models 3 (total output excluding subsidies, animal welfare index) and 4 (total output including agri-environmental and organic subsidies) also take into account environmental aspects of farm performance.

The animal welfare index in model 3 was calculated, based on 4 animal welfare indicators, derived from the survey data. They consist of a mixture of an outcome-based indicator, namely veterinary expenses as a proxy for animal health and resource-based measures, namely stable size as well as seasonal pasture and general outdoor access. Animal welfare promoting measures like grazing can also be associated with positive effects on farmland biodiversity, e.g. through more differential plant growth, leading to heterogenous patches (Benton et al., 2003).

With respect to the output definition in model 4, in the empirical literature, subsidies are usually not considered as part of the output, as they are not a physical output generated through the production technology (Minviel and Latruffe, 2017). This is in particular the case for direct payments from pillar one and LFA payments. However, recent research suggests that farms may be rationally inefficient (Hansson et al., 2018), meaning that they derive non-use values from e.g. the provision of public goods like enhanced animal welfare or farmland biodiversity. In this context, we follow Renner et al. (2021), arguing that ecological payments, based on voluntary agri-environmental measures reflect the monetary compensation for the provision of non-marketable goods by farmers like animal welfare or farmland biodiversity and are accompanied by adjustments of input levels of farmers.

Table1: Input and output definitions of DEA models

Model name	Output definition	Input definition
Model 1	Total output excluding subsidies (EUR)	Land (UAA in ha), labour (AWU), capital (EUR), intermediate expenses (EUR), herd size (LSU)
Model 2	Milk (kg), other output excluding milk (EUR)	
Model 3	Total output excl. subsidies (EUR), AWI	
Model 4	Total output including agri-environmental and organic subsidies (EUR)	

Note: AWI = animal welfare index, UAA = utilised agricultural area, AWU = agricultural working unit, LSU = livestock unit.

With respect to potential drivers of farm performance, the survey allowed us to collect information on a broad variety of variables, ranging from socio-economic characteristics of farmers (e.g. age, gender, education, whether the farming will be continued in the next 5 years), variables describing farm structure (share of rented land, share of estimated household income from farming, subsidies, measured as intensities (i.e EUR/ha UAA) and split up into direct payments from pillar one of the CAP, agri-environmental payments including those for organic farming and payments for less favoured areas (LFA). Finally, we investigate a set of further drivers, reflecting prices (milk price and rental prices for land) and agronomic conditions (altitude, share of forest area, a dummy for farms operating only on grassland and a regional dummy for Salzburg und Umgebung).

4.2.5 Results

4.2.5.1 Descriptive statistics

Table 2 provides an overview of the variables used for the DEA and potential drivers of technical-economic farm performance. Mean values for each variable were calculated for the whole sample and the 4 farm types. Conventional farms (n = 35) make up the biggest group, followed by organic haymilk farms (n = 20), organic farms (n = 16) and conventional haymilk farms (n = 10).

As can be seen from the descriptive statistics, conventional farms in our sample are on average the largest, followed by conventional haymilk farms, organic haymilk farms and organic farms. When looking at inputs, conventional farms also have the highest level of input-use. However, for the ecological farm types, the order is less clear in comparison to the outputs. It is for example noticeable that organic haymilk farms have the highest capital stock of ecological farm types, reflecting the higher costs for housing and production of hay, for which many farms have hay drying equipment, which raises capital costs. Organic farms on the other hand have the lowest value of capital stock and labour input. Also, intermediate expenses differ mainly between the two conventional and the two organic farm types.

Table2: Descriptive statistics of DEA variables and potential drivers of technical-economic and environmental farm performance

Variable	Whole sample (n = 81)	Conventional (n = 35)	Conventional haymilk (n=10)	Organic (n=16)	Organic haymilk (n=20)
Output(s) and inputs of DEA models					
Total output (EUR)	124,221.63	150,987.08	125,908.94	88,596.01	105,038.93
Milk (kg)	235,863.52	322,921.11	247,948.50	131,562.50	160,911.05
Other output excluding milk (EUR)	23,417.40	27,115.77	17,471.50	24,782.88	18,825.80
Subsidies (excluding investments (EUR)	21,622.41	19,949.73	21,489.97	22,912.42	23,583.82
Animal welfare index	0.48	0.37	0.40	0.59	0.61
Land (ha UAA)	35.64	38.59	36.15	34.11	31.44
Labour (AWU)	2.36	2.49	2.36	2.19	2.26
Capital (EUR)	610,567.79	662,852.11	595,547.82	499,548.28	615,395.82
Intermediate expenses (EUR)	50,383.07	62,408.40	61,541.18	36,118.00	35,171.75
Herd size (LSU)	62.46	72.93	70.86	45.29	53.66
Additional variables					
Male (dummy)	0.77	0.86	0.50	0.81	0.70
Higher education (dummy)	0.89	0.86	0.70	1.00	0.95
Age (years)	42.37	41.71	39.10	45.25	42.85
Continue farming (dummy)	0.90	0.80	1.00	0.94	1.00
Share of household income from farming	0.69	0.70	0.81	0.57	0.69
Share of rented land	0.38	0.38	0.36	0.32	0.42
Depreciation rate	0.58	0.56	0.63	0.59	0.57
Share of dairy cows from total cattle	0.57	0.56	0.59	0.57	0.57
Subsidies (EUR/ha UAA)	630.27	532.87	588.19	705.04	761.92
Subsidies pillar one (EUR/ha UAA)	273.66	283.90	268.46	266.55	264.02
Subsidies AES and organic (EUR/ha UAA)	260.60	137.37	268.22	304.18	437.58
Subsidies for LFA (EUR/ha UAA)	95.82	111.60	50.07	134.31	60.28
Share of forest area from total farmland	0.20	0.20	0.15	0.31	0.12
Altitude (m)	530.53	520.20	579.80	511.81	538.95
Permanent Grassland (dummy)	0.60	0.37	0.50	0.81	0.90
Salzburg und Umgebung (dummy)	0.48	0.26	1.00	0.12	0.90
Milk price (EUR/kg)	0.44	0.37	0.43	0.48	0.53
Rental price (EUR/ha)	307.12	287.67	424.94	207.40	362.01

Note: Values denote means.

4.2.5.2 Indicators of technical-economic and environmental farm performance

Table 3 shows a comparison of technical-economic and environmental farm performance indicators between the different farm types. Milk yield clearly reflects the expected differences between the ecological farm types. The profitability indicators indicate that all farm types can cover their costs on average, if opportunity costs regarding production factors are not considered. However, if opportunity costs are used to evaluate all production factors, farms can no longer cover their costs on average. As can be seen in the table, there are also differences between the ecological farm types, but these differences are not significant. Market orientation is around 80%, meaning that roughly 20% of revenues come from subsidies. The differences between the farm types are much smaller than for the profitability indicators, nevertheless they are statistically significant.

Table 3: Comparison of indicators of technical-economic and environmental farm performance

	Conventional (n = 35)	Conventional haymilk (n=10)	Organic (n=16)	Organic hay-milk (n=20)	Sig.
Indicators of technical-economic farm performance					
Milk yield (kg/cow)	8,120.81^{a,b,c}	6,784.94^{a}	6,275.16^{b}	6,142.41^{c}	***
Private RCR excluding opp. costs	1.37	1.25	1.23	1.37	
Public RCR excluding opp. costs	1.61	1.48	1.56	1.70	
Private RCR including opp. costs	0.72	0.62	0.60	0.65	
Public RCR including opp. costs	0.82	0.74	0.76	0.80	
Market orientation	0.84^{b,c}	0.83^{d}	0.79^{b}	0.80^{c}	**
Output per ha of UAA (EUR)	3,760.74^{b}	3,382.21	2,722.56^{b}	3,304.83	
Output per AWU (EUR)	62,586.97^{b}	54,062.03	42,457.22^{b}	47,842.32	
Output in relation to assets (EUR)	0.25^{c}	0.25	0.23	0.21^{c}	
Output in relation to interm. exp. (EUR)	2.58^{c}	2.26^{e}	2.68	3.17^{c}	.
Output per LSU (EUR)	1,986.22	1,735.53	1,979.55	1,946.99	
Eff. model 1 (output in EUR)	0.79	0.72	0.78	0.76	
Eff. model 2 (kg milk and other output in EUR)	0.81^{a,b,c}	0.69^{a}	0.72^{b}	0.63^{c}	***
Indicators of environmental farm performance					
Veterinary expenses (EUR / cow)	108.43^{b,c}	115.69	73.03^{b}	63.15^{c}	*
Stocking density (LSU/ha)	1.85^{b}	1.92^{d}	1.42^{b,d,f}	1.69^{f}	*
Seasonal pasture (days / year)	55.89^{b,c}	85.00	117.27^{b}	139.62^{c}	**
Outside (days / year)	74.78^{b,c}	66.96^{d,e}	171.06^{b,d}	174.27^{c,e}	***
Stable size (m² / LSU)	11.17^{b,c}	12.71	17.89^{b}	14.94^{c}	*
Animal welfare index (AWI)	0.37^{b,c}	0.40^{d,e}	0.59^{b,d}	0.60^{c,e}	***
Eff. model 3 (output1 and AWI)	0.85	0.83	0.88	0.89	
Subsidies agri-env and organic (EUR/ha)	137.37^{a,b,c}	268.22^{c,e}	304.18^{f}	437.58^{c,e,f}	***
Eff. model 4 (output incl. subsidies in EUR)	0.79	0.73	0.81	0.80	

Note: Sig. indicates a statistically significant difference of location parameters for at least one of the groups compared to all other groups, according to a Kruskal-Wallis rank sum test with ***, **, *, and . indicating significance at the 0.1%, 1%, 5% and 10% level, respectively. Additionally, ^{a,b,c,d,e,f} denote, whether differences are statistically significant at least at the 10% level or higher, when comparing two groups at a time, with the following notation: ^{a} = conventional vs. conventional haymilk, ^{b} = conventional vs. organic, ^{c} = conventional vs. organic haymilk, ^{d} = conventional haymilk vs. organic, ^{e} = conventional hay-milk vs. organic haymilk and ^{f} = organic vs. organic haymilk.

With respect to partial productivity indicators, some tendencies can be seen from the data. For example, conventional farms show statistically significant higher productivity with respect to land and labour compared to organic farms and also with respect to capital, compared to organic haymilk farms. Regarding intermediate expenses conventional haymilk farms seem to be less productive than organic and especially organic haymilk farms. Finally, output per LSU indicates no substantial differences.

In terms of efficiency indicators, we carried out calculations based on constant returns to scale (CRS) and variable returns to scale (VRS), but report only the VRS results, as a test between the two specifications showed that this specification better describes the production process. In order to ease interpretation, we calculated the inverse of output-oriented efficiencies, resulting in efficiency scores between 0 and 1, where 1 indicates a fully efficient farm.

Efficiency estimates based on the first output specification with aggregate market revenues indicate no statistically significant differences between groups. This changes however, when the differences in milk prices are taken out by including physical milk production as a separate output in the model together with other output measured in Euros. This indicates that milk yields cannot keep up if cows receive a diet consisting mainly of rough forage. At the same time, comparing these results with the first DEA model shows, that higher milk prices for haymilk, organic milk and organic haymilk compensate to some extent for lower milk yields.

For environmental farm performance indicators differences between the groups are mostly statistically significant and show the expected tendencies. The higher the degree of ecological approaches, the higher the performance level. However, if the AWI is considered as an additional output in DEA, results are significantly different only between conventional farms and organic haymilk farms as well as between conventional haymilk farms and organic haymilk farms.

For DEA model 4, the average efficiency scores of the groups are almost the same. Comparing these results with those of DEA models 1 and 2 shows that differences in efficiency between the groups are mostly eliminated by including subsidies in the aggregated output.

4.2.5.3 Drivers of technical-economic and environmental farm inefficiency

The results with respect to the drivers of technical-economic and environmental farm inefficiency can be found in Table 4. It needs to be noted that here the dependent variables are the original output orientated efficiency measures of the four DEA models, where a value of 1 denotes an efficient farm and a value greater than one an inefficient farm. Consequently, negative coefficients denote a positive effect on efficiency and vice versa. Despite the different dependent variables, there are several commonalities visible in the results across models.

Firstly, we find, ceteris paribus, a negative effect of male farm managers on efficiency in all models. Higher education is associated with higher efficiency in all models. For subsidies, we find a slight positive effect of intensity of pillar one payments in model 2 and a negative effect of AES and organic subsidies in models 2 and 3. The other subsidy variables are not significant. Also, AES and organic subsidies were not included in the regression based on results of DEA model 4, as in this model these payments are part of the output.

Results with respect to the degree of ecological approaches adopted by farms show that all of the ecological farm types tend to have a negative effect on efficiency. The negative effect is most pronounced for conventional haymilk farms, where it is significant in all models, while for organic farms the effect is only significant in model 4. For organic haymilk farms the effect is not significant in model 3, but significant in all other models.

Moving on to farm structural variables, a higher share of dairy cows from total cattle is associated with a higher efficiency level, indicating that higher specialised dairy farms tend to be more efficient. The same trend can be seen when looking at the share of household income from farming, where the coefficient is significant in models 3 and 4. In contrast to that, farms with a higher share of rented land tend to be less efficient.

When investigating prices as drivers of efficiency, results show that both, higher milk prices and higher rental prices for land are associated with higher efficiency. Note that we did not include milk prices as driver in the regression based on model 2, as in this model efficiency with respect to milk production only depends on the quantity of milk.

Finally, the other drivers, controlling for site conditions and location are not statistically significant, with the exception of altitude in model 3. This means when considering the above-mentioned drivers, site conditions have predominantly no further statistically significant effect on efficiency estimates.

Table 4: Results of second stage truncated regression: drivers of inefficiency

Model description	**Eff. model 1 (aggregated market revenue in EUR))**		**Eff. model 2 (milk in kg and other market revenue in EUR)**		**Eff. model 3 (output 1 and AWI)**		**Eff. model 4 (market revenues including subsidies in EUR)**	
Variable	**Coefficients and statistical significance levels**							
Intercept	6.2892	*	3.3344	*	6.0524	*	5.6829	*
Male (dummy)	0.7442	*	0.6994	*	0.3573	*	0.5930	*
Higher education (dummy)	-0.386	*	-0.3755	*	-0.2694	*	-0.3207	*
Age (years)	-0.0065		-0.006		0.0046		-0.0019	
Continue farming (dummy)	-0.3126		-0.6279	*	0.3442	*	-0.1926	
Subsidies pillar one (EUR/ha UAA)	-0.0031		-0.0045	*	0.0005		-0.0012	
Subsidies AES and organic (EUR/ha UAA)	0.0019		0.0022	*	0.0017	*	*NA*	
Subsidies for LFA (EUR/ha UAA)	0.0006		0.0026	*	0.0003		0.0003	
Conventional haymilk farm (dummy)	1.1696	*	0.8759	*	0.7938	*	1.1402	*
Organic farm (dummy)	0.4285		0.0998		0.3076		0.5389	*
Organic haymilk farm (dummy)	1.1578	*	0.4376		0.6633	*	1.2946	*
Share of dairy cows from total cattle	-1.7087	*	-1.3993	*	-2.5701	*	-1.7777	*
Share of household income from farming	-0.4163		-0.2181		-1.0441	*	-0.4931	*
Share of rented land	0.7203	*	0.798	*	0.3752	*	0.5752	*
Depreciation rate	0.6663		0.073		-0.2275		0.5518	
Milk price (EUR/kg)	-7.838	*	*NA*		-7.6917	*	-7.1911	*
Rental price (EUR/ha)	-0.0025	*	-0.0014		-0.0012	*	-0.0021	*
Share of forest area from total farmland	0.0936		-0.1132		0.1304		0.0543	
Altitude (m)	-0.0008		-0.0009		-0.0014	*	-0.0006	
Permanent Grassland (dummy)	-0.1373		-0.0657		-0.1309		-0.0787	
Salzburg und Umgebung (dummy)	0.1518		0.2991		0.1794		0.1991	

Note: * indicates significance at the 5% level or higher.

4.2.6 Discussion and conclusions

Our results indicate that more extensive dairy farming systems perform better in terms of environmental outputs and animal welfare. Additionally, they can compete from an economic point of view to some extent with more intensive systems.

Several aspects need to be considered, when interpreting our results. Firstly, our sample is not representative for the farm population in the two regions according to some key variables (e.g. larger farm size). However, such professionally led 'model farms' show what is possible in the respective production system, serving possibly also as role models for other farmers. From a methodological point of view, including more than one output in an output-orientated DEA model gives farms more possibilities to become efficient, which can be seen, when comparing e.g. results of model three with those of models one, two and four, respectively. Finally, due to the limited size of the sample and the subgroups of ecological farm types, we could not consider additional methodological possibilities like matching or separate production technologies for the respective farm types to account for possible biases due to sample selection or differences in production technology between the groups.

Given these limitations, our analysis can still provide very detailed regional insights into these 4 dairy farming systems. Also, due to the regional focus our results are more ground-truth. We intensively discussed our results with regional stakeholders and farmers, who agreed with our findings and confirmed that they reflect what is occurring in the regions.

Given the unique situation in Austria and the case study region with an already very advanced ecological transition of dairy farms, we draw the following conclusions based on our results and exchanges with regional stakeholders. Public payments for public goods provided by dairy farms, together with higher market prices for their market goods seem to be able to offset a decrease in production of market goods to a substantial degree. The possible exceptions are conventional haymilk farms, which seem to perform slightly worse, compared to the other ecological farm types. Possibly, this form of milk production is not distinct enough, as it does not yet profit from the positive brand image of organic farming, which is very popular in Austria, reflected also in higher prices for organic products. However, it needs to be noted that this group of farms was also the smallest group in our sample, consisting only of 10 farms.

Sustainable economic success of more ecological farming systems requires the right framework conditions, in our case acceptance of the respective ecological farm type and its products by society, demand for their products by retailers and consumers, reflected in adequate market prices and finally also public support.

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4.3 Technical-economic and environmental performance of Austrian dairy farms (BOKU)

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4.3.1 Introduction

The aim of the present study is to investigate and compare farm performance of different dairy farming systems, going beyond a comparison of only conventional and organic farms with broadly available European FADN data. Austria is a particularly interesting case for such an analysis, as it has already undergone a very dynamic ecological transition of the farming sector.

Methodologically our study consists of the following steps: firstly, we identify different ecological dairy farming systems using the FADN protocol for the LIFT farm typology (Rega et al., 2019; Thompson et al., 2021; Rega et al., 2021). Secondly, we calculate various simple and more sophisticated indicators to analyse and compare technical-economic and environmental farm performance of the identified systems. In order to control for certain biases in such a comparison, we employ a matching procedure to control for selection bias and a Data Envelopment Analysis (DEA) based meta frontier of production possibilities to identify performance gaps. Finally, we analyse several drivers of technical-economic and environmental farm performance with econometric methods. Our results show potential synergies and trade-offs in terms of economic and environmental performance of the identified farming systems and of switching to a more ecological farming system.

4.3.2 Description of case study region

With exception of the Danube valley and the north-eastern and south-eastern plains, Austria is dominated by mountains, making up roughly 64% of the total area. These areas are dominated by forests and permanent grasslands and farms have consequently specialised on grazing livestock husbandry. Dairy farms and more extensive grazing livestock farms, are the most common farm types in these regions. In total, specialist grazing livestock farms make up around 45% of all farms in Austria, of which roughly half (24%) deliver milk to dairies (Federal Ministry of Agriculture, Regions and Tourism, 2020). Dairy farms in Austria are mostly family farms with an average of around 22 dairy cows, a total number of livestock units of about 36 and roughly 33 ha of utilised agricultural area (UAA), which is mostly permanent grassland. Dual use breeds are dominating and the average milk yield is around 7,800 kg per dairy cow. These farms also often generate additional revenue from forestry and other gainful activities including for example the provision of (machinery) services or agro-tourism, additionally to dairy farming (LBG, 2020).

In terms of degree of ecological approaches in the farming sector, many dairy farms in Austria have already converted to organic farming as a more extensive form of agricultural production. Austria has the highest share of organic farms in the EU (18.3% in 2017) and the share of organic farms with milk delivery is even higher (25.5% in 2017) (Federal Ministry of Agriculture, Regions and Tourism, 2020). The organic farming sector in Austria experienced a very dynamic development in the 1990s, shortly before and after Austria joined the EU in 1995 with a growth from around 2,000 organic farms in 1992 to around 20,000 organic farms in 1998. This successful transition to organic farming was supported by government subsidies and a successful development of organic products and brands as well as their broad acceptance by large food chains and supermarkets (Vogl and Hess, 1999). After this period of huge growth, the number of organic farms developed less dynamically and reached around 24,000 farms in 2019. This is still considerable, if one takes into account structural change, characterised by a steady decline of the total number of farms from about 160,000 in 2000 to around 120,000 in 2019 (Federal Ministry of Agriculture, Regions and Tourism, 2020).

4.3.3 Method

Our methodological approach in this study consists of four steps: (i) identification of different ecological farming systems, (ii) calculation of performance indicators (iii) comparison of performance indicators between groups and (iv) analysis of drivers of farm performance. Some of the used performance indicators, the method of efficiency estimation and the in- and output definitions for efficiency estimation are similar to the study in chapter 4.2. A more detailed description of these aspects can be found there.

We identify different ecological farming systems, using the protocol for the LIFT farm typology (Rega et al., 2019; Rega et al., 2021) and a computer program to implement the protocol (Thompson et al., 2021). As of now, the protocol allows to identify the following farming systems: (i) low input farms are characterised by a low level of input use, (ii) integrated farms are characterised by a high degree of circularity in their input use and (iii) organic farms, are farms that are either partially or fully certified as organic farms according to FADN data. While the classification of organic farms is straight forward, for the classification of low input and integrated systems requires first the calculation of several indicators and total scores for each farming system are then calculated based on a weighted average of the individual variable scores. The methodology is designed in a way that farms can belong to more than one farming system at the same time (e.g. low input, integrated and organic). In contrast, standard farms are those farms, which do not belong to any of the other farming systems.

A wide range of farm performance indicators are calculated in this analysis. In terms of technical-economic performance we investigate indicators related to profitability, partial productivity and efficiency, as well as two additional indicators, measuring the market orientation and financial stability of farms, respectively. With respect to environmental performance indicators, FADN data only provides limited information. We mainly use intensities of inputs related to negative environmental externalities on the one hand and environmental subsidies as a proxy for the amount of public goods produced by farms. While this latter approach is far from accurate, it is nevertheless a useful approximation for measuring the provision of public goods by farms.

Profitability indicators are calculated as revenue cost ratio (RCR), where a ratio greater than one means that a farm is profitable. A detailed description of the RCRs can be found in the methods section of chapter 4.2. Additionally, we consider three more profitability indicators from FADN data, namely gross farm income per AWU, farm net value added per AWU and farm net income per AWU of unpaid family labour. Partial productivities are calculated as average products by dividing the total output of the farm by the individual inputs. Market orientation measures the share of subsidies of total output plus subsidies and is a measure of dependence from public payments. Finally, the equity ratio is calculated by dividing total liabilities through total assets and is an indicator for financial stability.

Efficiency indicators consider all inputs and outputs of the production process jointly and thus allow to assess overall productivity of farms compared to benchmark farms as a relative measure. We use Data Envelopment Analysis (DEA) as a method to estimate efficiency of farms. More details on DEA can be found in the methods section of chapter 4.2. For the present analysis, we again choose an output-oriented model and assume variable returns to scale (VRS). The bigger size of our FADN sample allows us to use some further methods, aimed at addressing certain biases, when comparing farm performance of the different farming systems.

Firstly, in order to address a possible sample selection bias due to structural differences between farming systems, we use matching. The basic idea of matching is to find comparable farms based on observed factors in order to create a valid counter factual and then compare performance of matched farms (Ho et al., 2007). In this analysis, we use direct covariate matching (DCM), where matching is performed upon several covariates at the same time. As matching algorithm, we use nearest neighbour matching with replacement. A statistical comparison of matching covariates before and after matching is then carried out in order to test, whether structural differences between the groups have been successfully eliminated. After matching, causal inference in terms of comparison of farm performance between groups is made by computing the average treatment effect on the treated (ATT).

Another possibly restrictive assumption is that farms in different farming systems all operate under the same production technology. If this is not the case, part of the estimated inefficiency might be related to performance gaps due to technological constraints or regulations associated with individual farming systems and not actual inefficiency. We therefore further use the metafrontier framework of O'Donnell et al. (2008), which allows to split up efficiency into a part related to differences in technology, the so-called metatechnology ratio (MTR), and a second part related to actual inefficiency. MTRs also help to show which farming system has the most productive technology.

Finally, drivers of farm performance are assessed with econometric methods. Specifically, we use the double bootstrap procedure of Simar and Wilson (2007). Calculations are done in R (R Development Core Team, 2021) and the package {rDEA} (Simm and Besstremyannaya, 2020).

4.3.4 Data

Our FADN dataset consists of an unbalanced panel of specialised dairy farms (TF14 = 45). Upon inspecting the data, we removed some observations with very unusual input-output combinations. Our panel dataset then contains 1,583 observations and 853 farms over both years as well as 796 farms in 2014 and 787 farms in 2015. All monetary values are deflated with price indices to account for price differences between the two years.

We calculate three different DEA models in total, all with the same definitions of inputs, but different definitions of outputs (see Table 1). We use the five inputs land (in ha UAA), labour (in annual working units – AWU), capital (end of the year value of assets minus value of land and livestock, as both are included as separate outputs), intermediate expenses (e.g. for feed, energy, etc. in Euros) and herd size (in livestock units – LSU) in all DEA models.

Table 1: Input and output definitions of DEA models

Model name	Output definition	Input definition
Model 1	Total output excluding subsidies (EUR)	Land (UAA in ha), labour (AWU), capital (EUR), intermediate expenses (EUR), herd size (LSU)
Model 2	Milk (kg), other output excluding milk (EUR)	
Model 3	Total output including agri-environmental and organic subsidies (EUR)	

Note: AWI = animal welfare index, UAA = utilised agricultural area, AWU = annual working unit, LSU = livestock unit.

Outputs in model 1 (total output excluding subsidies in EUR) and model 2 (milk in kg, other output in EUR) reflect technical-economic farm performance, while output in model 3 (total output including agri-environmental and organic subsidies) reflects also environmental farm performance due to the inclusion of environmental payments. A more detailed argumentation, why we include environmental payments in the output can be found in the data section of chapter 4.2.

With respect to potential drivers of farm performance, FADN data only provides limited information compared to the LIFT farmer survey. For example, there is no information on socio-economic characteristics of farmers in the data provided by the EU for LIFT. We therefore focussed our analysis on variables describing site conditions, farm structure (share of permanent grassland, share of dairy cows from total LSU, share of rented land, debt ratio) and subsidies. We split up subsidies into three components (decoupled subsidies, LFA subsidies and rural development subsidies), expressing them all as intensities (i.e EUR/LSU). Rural development (RD) subsidies contain all RD payments, except LFA and investment subsidies. These RD payments mostly stem from the very broad and well-accepted Austrian agri-environmental program (ÖPUL) and subsidies for organic farming and can thus be considered as payments for the provision of public goods by agriculture (e.g. farmland biodiversity or animal welfare).

4.3.5 Results

4.3.5.1 LIFT farm typology

Results of the application of the LIFT farm typology to our pooled sample of specialised dairy farms (n = 1583, t = 2014-2015) are depicted in Figure 1.

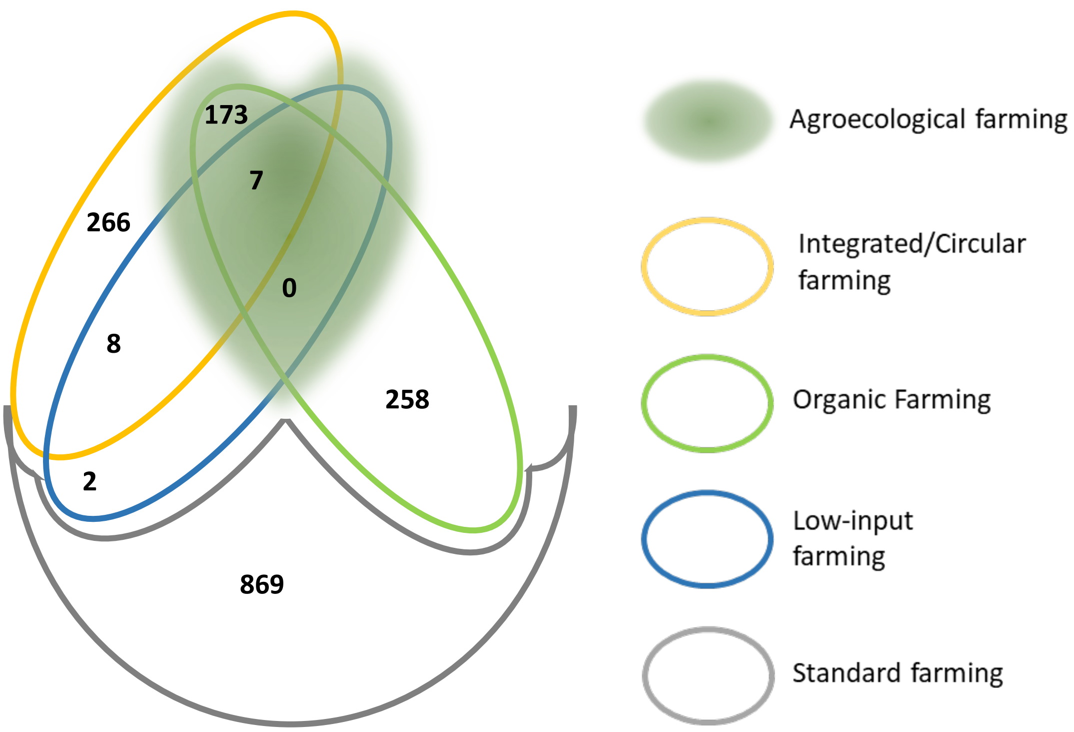

Figure1: LIFT farm typology applied to the pooled panel of Austrian dairy farms (n = 1583, t = 2014-2015)

As the number of farms classified as low input or a combination of low input and other farming systems is too low for a meaningful statistical analysis, we decided not to classify these farms in separate groups. Instead, we added them to the other groups, they overlapped with and in the case of the 2 farms, which were only classified as low input, we added them to the group of standard farms. Thus, in our final categorisation the total number of 1583 observations in both years is distributed as follows: 871 observations are classified as standard farms, which we consider as the most intensive and from an environmental point of view unrestricted production system, followed by 274 observations being classified as integrated farms, characterised by a higher degree of circularity of input use. Next, 258 observations are organic farms, which comply with the standards of organic farming and 184 observations are integrated organic farms, combining a high circularity of input use and the standards of organic farming, which we consider as the most ecological farming system.

4.3.5.2 Descriptive statistics

Table 2 provides an overview of the variables used for the DEA and additional variables, describing our sample. Arithmetic means as well as coefficients of variation (CV) were calculated for the whole sample and the 4 farm types.

Looking at the in- and outputs it becomes evident, that standard farms are on average the largest, while integrated farms are by far the smallest. There is a similar trend for organic and integrated organic farms. While both groups are smaller in terms of inputs and outputs compared to standard farms, they are still bigger than integrated farms and integrated organic farms are not that much smaller compared to organic farms. These differences in size also manifest in the degree of specialisation of the farms, reflected in the share of dairy output from total output. Regarding milk yield, organic and both integrated farming groups have a more extensive dairy husbandry system. It is the other way around with milk prices. A similar trend can be seen for subsidies.

Table 2: Descriptive statistics of DEA variables and selected additional variables

Variable	**Whole sample (n = 1,583)**	**Standard (n = 871)**	**Integrated (n=274)**	**Organic (n=258)**	**Integrated-Organic (n=180)**
Output(s) and inputs of DEA models					
Total output excl. AE subsidies (TEUR)	100.04 (0.63)	118.10 (0.56)	57.72 (0.61)	99.50 (0.57)	77.80 (0.53)
Milk (t)	162.12 (0.75)	206.06 (0.65)	83.41 (0.58)	142.27 (0.65)	97.81 (0.58)
Other output (TEUR)	42.55 (0.68)	47.99 (0.62)	30.36 (0.83)	40.63 (0.68)	37.56 (0.65)
Total output including AE subsidies (TEUR)	106.39 (0.61)	122.98 (0.55)	62.19 (0.60)	109.85 (0.55)	88.44 (0.52)
Land (ha UAA)	31.02 (0.70)	31.94 (0.58)	24.99 (0.82)	30.37 (0.80)	36.68 (0.84)
Labour (AWU)	1.95 (0.33)	2.04 (0.31)	1.71 (0.35)	1.93 (0.34)	1.95 (0.34)
Capital (TEUR)	536.44 (0.54)	574.06 (0.52)	413.52 (0.65)	559.86 (0.50)	507.94 (0.51)
Intermediate expenses (TEUR)	55.50(0.62)	67.10 (0.55)	31.31 (0.49)	54.71 (0.52)	37.28 (0.46)
Herd size (LU)	39.05 (0.59)	45.96 (0.54)	25.99 (0.47)	36.03 (0.54)	29.83 (0.54)
Additional variables					
Share of dairy output from total output	0.56 (0.27)	0.58 (0.24)	0.49 (0.29)	0.58 (0.26)	0.52 (0.31)
Milk yield (t/cow)	6.55 (0.23)	7.25 (0.19)	5.51 (0.21)	6.09 (0.21)	5.36 (0.17)
Milk price (EUR/kg)	0.36 (0.17)	0.34 (0.12)	0.33 (0.09)	0.41 (0.12)	0.40 (0.22)
Total operational subsidies (TEUR)	21.43 (0.55)	21.30 (0.54)	15.63 (0.53)	25.55 (0.49)	24.95 (0.52)
Decoupled subsidies (EUR/LSU)	226.10 (0.33)	225.99 (0.31)	240.42 (0.36)	202.08 (0.26)	239.25 (0.42)
LFA subsidies (EUR/LSU)	152.96 (0.91)	117.90 (0.91)	170.30 (0.75)	202.21 (0.86)	225.65 (0.78)
RD subsidies excl. LFA and Inv. (EUR/LSU)	191.30 (0.75)	120.80 (0.77)	186.36 (0.63)	305.61 (0.40)	376.10 (0.37)
Share of dairy cows from total LSU	0.60 (0.17)	0.60 (0.17)	0.57 (0.19)	0.62 (0.16)	0.61 (0.18)
Share of rented land from total land	0.30 (0.83)	0.34 (0.74)	0.22 (0.91)	0.28 (0.86)	0.25 (1.00)
Debt ratio	0.12 (1.83)	0.15 (1.67)	0.07 (2.00)	0.13 (1.46)	0.09 (2.22)
Share of permanent grassland	0.89 (0.17)	0.87 (0.18)	0.86 (0.17)	0.96 (0.08)	0.91 (0.15)
Share of farms above 600 m	0.57	0.49	0.56	0.76	0.66
Share of farms in LFA	0.90	0.87	0.89	0.97	0.98

Note: Values denote means, values in parenthesis denote coefficients of variation (CV).

4.3.5.3 Indicators of technical-economic and environmental farm performance

Table 3 shows results of farm technical-economic and environmental performance indicators. A simple comparison of means, based on a one-way analysis of variance (ANOVA) indicates a substantial degree of heterogeneity between the 4 farming systems, as the differences are all significant at the 0.1% level.

Table 3: Mean comparison of technical-economic and environmental performance indicators

Performance indicators	Standard (n = 871)	Integrated (n=274)	Organic (n=258)	Integrated-Organic (n=180)	Sig.
Technical-economic performance indicators					
Private RCR excluding opp. costs	1.21	1.18	1.2	1.3	***
Public RCR excluding opp. costs	1.45	1.52	1.54	1.73	***
Private RCR including opp. costs	0.65	0.5	0.61	0.57	***
Public RCR including opp. costs	0.77	0.64	0.77	0.75	***
Market orientation	0.83	0.77	0.78	0.75	***
Equity ratio	0.92	0.99	0.92	0.96	***
Output (EUR) per ha of UAA	3,924.2	2,570.88	3,694.44	2,489.05	***
Output (EUR) per AWU	58,163.19	35,390.99	51,828.42	40,877.35	***
Output (EUR) in relation to assets	0.22	0.16	0.19	0.16	***
Output (EUR) in relation to intermediate exp.	1.77	1.81	1.83	2.08	***
Output (EUR) per LSU	2,623.67	2,271.01	2,781.36	2,736.83	***
Gross farm income (EUR) per AWU	34594.62	25116.54	36353.64	34743.62	***
Farm net value added (EUR) per AWU	21784.09	15420.03	23737.44	23791.47	***
Farm net income (EUR) per AWU	17519.31	12751.43	19860.98	20990.74	***
Eff. model 1 (output in EUR)	0.62	0.55	0.59	0.59	***
Eff. model 2 (kg milk and other output in EUR)	0.71	0.63	0.62	0.62	***
Environmental performance indicators					
Stocking density (LSU/ha)	1.77	1.37	1.37	1.04	***
Veterinary expenses (EUR / cow)	108.9	82.99	92.01	64.41	***
Fertiliser costs per ha (EUR)	61.81	25.88	15.58	8.59	***
Crop protection costs per ha (EUR)	16.86	9.58	1.08	1.59	***
Concentrate feed costs per ha (EUR)	485.19	265.41	487.49	256.21	***
RD subsidies (excl. LFA and Inv.) (EUR/ha)	120.8	186.36	305.61	376.1	***
Eff. model 3 (output incl. RD subsidies in EUR)	0.62	0.56	0.62	0.63	***

Note: Sig. indicates a statistically significant difference based on a oneway ANOVA with ***, **, *, and denoting the 0.1%, 1%, 5% and 10% level, respectively.

However, as a simple comparison of means might be biased, we will focus primarily on ATTs after matching. Structural differences between the groups were considered in terms of farm size (measured by standard output), site conditions (proxied by LFA payments per LSU and the share of permanent grassland) and a dummy for the year 2014 (matched farms had to be from the same year). Results are depicted in Table 4. In the upper part of the table, means of the matching variables before and after matching show that structural differences between the groups were successfully eliminated by matching. However, this comes at a cost, as at the same time the number of matched farms decreased significantly. One may say this reduction in sample size is problematic as it biases our matched sample, but at the same time this allows us to compare farms of the different farming systems of similar size and facing similar site conditions.

Table 4: Comparison of matching variables and ATT of technical-economic and environmental performance indicators between groups

	Means Conv|Int	Sig.	Means Conv|Org	Sig.	Means Conv|Int_Org	Sig.	Means Int→Org	Sig.	Means Int|Int_Org	Sig.	Means Org|int_Org	Sig.
Standard output (TEUR) before matching	88.6|50.6	***	88.6|70.4	***	88.6|60.4	***	50.6|70.4	***	50.6|60.4	***	70.4|60.4	**
Standard output (TEUR) after matching	49.6|49.8	.	55.7|55.8		49.8|50.2		44.2|44.1		40.5|40.5		44.3|44.6	
LFA subsidies (TEUR) before matching	4.1|3.8	**	4.15|5.6	***	4.1|5.6	***	3.8|5.6		3.8|5.6	***	5.6|5.6	
LFA subsidies (TEUR) after matching	4.2|4.2		4.92|4.9		4.8|4.8		5.0|5.0		4.9|5.0		5.2|5.2	
Share of perm. grassland before matching	0.87|0.86	*	0.87|0.96	***	0.87|0.91	***	0.86|0.96	***	0.86|0.91	***	0.96|0.91	***
Share of perm. grassland after matching	0.96|0.96		0.99|0.99		0.99|0.99		0.99|0.99		0.98|0.98		0.99|0.99	
Number of farms in each group	871|274		871|258		871|180		274|258		274|180		258|180	
Number of matched farms	76		103		60		39		29		42	
Performance indicators	**ATT Conv→Int**	**Sig.**	**ATT Conv→Org**	**Sig.**	**ATT Conv→Org_Int**	**Sig.**	**ATT Int →Org**	**Sig.**	**ATT Int→Int_Org**	**Sig.**	**ATT Org→int_Org**	**Sig.**
Technical-economic performance indicators												
Private RCR excluding opp. costs	0.11	***	0.04	*	0.18	***	-0.08	***	0.07	***	0.16	***
Public RCR excluding opp. costs	0.20	***	0.12	***	0.37	***	-0.06	***	0.16	***	0.24	***
Private RCR including opp. costs	-0.03	***	0.00		0.00		0.01		0.03	***	-0.01	
Public RCR including opp. costs	-0.02	.	0.04	***	0.06	***	0.02	***	0.06	***	0.00	
Market orientation	-0.03	***	-0.04	***	-0.07	***	-0.02	***	-0.03	***	-0.02	***
Equity ratio	0.02	**	0.00		0.01		-0.03	***	-0.03	***	0.09	***
Output (EUR) per ha of UAA	-1,046	***	-555	***	-1,745	***	626	***	-359	***	-1,079	***
Output (EUR) per AWU	-6,962	***	-253		-1,744	.	3,079	***	3,613	***	-5,823	***
Output (EUR) in relation to assets	-0.03	***	-0.01	.	-0.02	***	0.03	***	0.01	**	-0.01	***
Output (EUR) in relation to interm. exp.	0.24	***	0.10	***	0.38	***	-0.16	***	0.23	***	0.34	***
Output (EUR/LSU)	-243	***	-45		-117	*	144	***	216	***	-82	
Gross farm income (EUR/AWU)	-512		4,846	***	8,686	***	860	*	6,677	***	231	
Farm net value added (EUR/AWU)	470		4,353	***	8,723	***	215		5,839	***	1,095	
Farm net income (EUR/AWU)	1,154	.	2,980	***	9,068	***	438		6,099	***	998	
Eff. model 1 (output in EUR)	0.00		0.01		0.02	***	-0.02	***	0.03	***	0.03	***
Eff. model 2 (kg milk and other output in EUR)	-0.03	***	-0.07	***	-0.07	***	-0.02	***	-0.01	*	0.03	***
Environmental performance indicators												
Stocking density (LSU/ha)	-0.31	***	-0.21	***	-0.63	***	0.14	***	-0.25	***	-0.33	***
Veterinary expenses (EUR / cow)	-39	***	-33	***	-67	***	39	***	-24	***	-13	***
Fertiliser costs EUR/ha)	-20	***	-4.85	**	-20	***	-0.42		-5.91	***	-6.63	***
Crop protection costs EUR/ha)	0.85		-3.72	***	-2.90	***	-3.73	***	-2.48	***	-0.12	***
Concentrate feed costs (EUR/ha)	-201	***	-11		-285	***	196	***	-65	***	-212	***
RD subsidies (excl. LFA and Inv.) (EUR/ha)	66	***	158	***	254	***	95	***	169	***	89	***
Eff. model 3 (output incl. RD subsidies in EUR)	0.00		0.03	***	0.07	***	0.00		0.06	***	0.05	***

Note: sig. indicates a statistically significant difference of ATT with ***, **, *, and . indicating significance at the 0.1%, 1%, 5% and 10% level, respectively.

ATTs in the lower part of the table were calculated by comparing each of the groups pairwise to one another, whereby the less ecological farming system was always defined as the control group and the more ecological farming system as the treated group. A positive ATT thus indicates that the respective indicator increases, when switching to a more ecological farming system, while a negative ATT indicates the opposite. This results in a total of 6 comparisons, namely (a) standard → integrated, (b) standard → organic, (c) standard → integrated organic, (d) integrated → organic, (e) integrated → integrated organic and (f) organic → integrated organic. These comparisons are able to identify performance gaps between the different farming systems for the performance indicators.

Overall, the standard integrated farming system tends to perform worse compared to the other groups. While this farming system performs better in terms of environmental performance compared to the standard system, it performs worse, when looking at technical economic performance. In contrast, organic and integrated organic farming systems can compete with standard farms in terms of profitability, especially, if subsidies are included. At the same time, these farming systems also perform better in terms of environmental performance than the standard system and also than the integrated system. Switching from organic to an integrated organic farming system does not lead to further economic drawbacks, while environmental performance clearly increases further.

Up until now, we have assumed that all farms operate under the same production technology, when comparing efficiencies between the groups. Table 5 shows efficiency results, if we assume different production technologies for each group instead. For standard farms, most of the inefficiency is due to inefficiency within their respective groups, and the MTRs are consequently very high for all 3 models. For the other farming systems, more inefficiency is attributable to a potential technology gap, as is visible by the lower MTRs.

Table 5: Comparison of group efficiencies, metatechnology ratios and metafrontier efficiencies

Efficiency measure	Standard (n = 871)	Integrated (n=274)	Organic (n=258)	Integrated-Organic (n=180)
Efficiency with respect to group frontier				
Eff. model 1(output in EUR)	0.65	0.60	0.68	0.66
Eff. model 2 (kg milk and other output in EUR)	0.73	0.72	0.75	0.77
Eff. model 3 (output incl. RD subsidies in EUR)	0.66	0.62	0.69	0.69
Metatechnology ratio (MTR)				
Eff. model 1(output in EUR)	0.96	0.92	0.86	0.89
Eff. model 2 (kg milk and other output in EUR)	0.98	0.88	0.83	0.81
Eff. model 3 (output incl. RD subsidies in EUR)	0.94	0.90	0.90	0.92
Efficiency with respect to metafrontier				
Eff. model 1(output in EUR)	0.62	0.55	0.59	0.59
Eff. model 2 (kg milk and other output in EUR)	0.71	0.63	0.62	0.62
Eff. model 3 (output incl. RD subsidies in EUR)	0.62	0.56	0.62	0.63

4.3.5.4 Drivers of technical-economic and environmental farm inefficiency

Table 6 shows the results of double bootstrap truncated regression analysis of drivers with respect to efficiencies related to the respective group frontiers. This leads to a total of 12 regression models, one for each DEA model and farming system. As the regression analyses are calculated with the actual output orientated efficiency measures (which is in fact an inefficiency score) and not their inverse, a positive sign of coefficients in these models indicates a negative effect on efficiency, whereas a negative sign of coefficients indicates a positive effect on efficiency.

Table 6: Results of second stage analysis of drivers of farm inefficiency

Model description	Standard (n = 871)		Integrated (n=274)		Organic (n=258)		Integrated-Organic (n=180)	
Variable	**Coefficients and statistical significance levels**							
Model 1 (Total output excluding subsidies)								
Intercept	3.413	*	4.237		-8.243		-6.188	
Share of permanent grassland	0.034		-0.158		2.836		1.919	*
Decoupled subsidies (EUR/LSU)	-0.223	*	0.075		0.653		0.263	
LFA subsidies (EUR/LSU)	0.102	*	0.081		0.575	*	0.209	
RD subsidies excl. LFA and Inv. (EUR/LSU)	0.059	*	-0.007		-0.194		-0.188	
Share of dairy cows from total cattle	-0.298	*	-0.673	*	-2.281	*	-0.618	*
Share of rented land	-0.087	*	0.009		-0.075		0.027	
Debt ratio	0.001		0.057		0.087		-0.095	
Dummy year 2014	-0.295	*	-0.101		-0.051		-0.04	
Model 2 (Milk output and other output)								
Intercept	6.486	*	7.391	*	2.732		2.985	*
Share of permanent grassland	-0.165	*	-0.297		0.58		0.597	*
Decoupled subsidies (EUR/LSU)	-0.152	*	-0.089		0.13		-0.174	
LFA subsidies (EUR/LSU)	0.058	*	0.018		0.132	*	-0.014	
RD subsidies excl. LFA and Inv. (EUR/LSU)	0.036	*	0.061		0.132		0.306	*
Share of dairy cows from total cattle	-0.928	*	-1.131	*	-1.513	*	-1.277	*
Share of rented land	-0.043	*	-0.034	*	-0.022		0.016	
Debt ratio	0.007		0.038		0.039	*	0.002	
Dummy year 2014	-0.16	*	-0.088		-0.12	*	-0.137	*
Model 3 (Total output including subsidies))								
Intercept	3.474	*	4.728	*	-0.451		-4.229	
Share of permanent grassland	0.011		-0.325		0.805		1.325	*
Decoupled subsidies (EUR/LSU)	-0.185	*	0.045		0.255		0.151	
LFA subsidies (EUR/LSU)	0.077	*	0.046		0.184	*	0.12	
Share of dairy cows from total cattle	-0.254	*	-0.542	*	-0.993	*	-0.44	
Share of rented land	-0.079	*	0.01		-0.059	*	0.011	
Debt ratio	-0.001		0.053		0.037		-0.056	
Dummy year 2014	-0.266	*	-0.184		-0.126		-0.073	

Note: * indicates that the 2.5% and 97.5% confidence interval of the respective coefficient does not contain zero.

It is clearly visible that standard farms have the highest number of statistically significant drivers throughout all models. However, this may be also related to the higher number of observations in this group, compared to the others. For this group, higher decoupled subsidies are associated with higher efficiency, whereas higher LFA and RD subsidies are associated with lower efficiency. Interestingly, in model 2, a higher share of grassland is also related to higher efficiency scores. A higher share of dairy cows from total livestock units, indicates a higher degree of specialisation of dairy farms and is consequently also related to higher efficiency. The same is true for the share of rented land. Finally, the 2014 dummy indicates that this year was more productive, than 2015.

For the other farming systems, less drivers are significant throughout the models. One variable, namely the share of dairy cows, shows a positive relation to efficiency throughout all farming systems and models, except for integrated organic farms in model 3. There are no clear trends throughout the farming systems and models for the other drivers. For integrated farms the share of rented land has a positive effect on efficiency in model 2. The other drivers are not significant for integrated farms. LFA subsidies again show a negative effect on efficiency for organic farms in all models. In model 2 a higher debt ratio is also associated with lower efficiency, whereas the dummy for the year 2014 has a positive effect on efficiency. Additionally, in model 3 a higher share of rented land has a positive effect on efficiency. Finally, we look at the results for integrated organic farms. Here, a higher share of permanent grassland shows a negative effect on efficiency in all three models. Additionally, in model 2, a higher level of RD subsidies is also associated with lower efficiency.

4.3.6 Discussion and conclusions

In terms of data source, we want to point out two issues. Firstly, FADN data provides only limited data on environmental performance of farms and we thus relied on proxies. In the medium to long run it would thus be very beneficial to add more environmental data in FADN, which are already collected for other purposes (e.g. in the IACS). For example, it would already be very beneficial to better differentiate grassland areas in terms of their intensity of use (e.g. number of cuts).

A second issue is that the land variable in our analysis, measured as hectare of UAA is problematic, when farms have large shares of their land in disadvantaged mountainous areas (e.g. alpine pastures, or other very extensive grasslands). In Austrian FADN data, such areas are multiplied with a reduction factor smaller than one, leading to a reduced measure of farm size in terms of land, which better reflects the biophysical production possibilities. Direct payments are also based on this reduced land measure. Adding a similarly adapted land variable to the European FADN data would certainly also be beneficial for future analyses of farm performance with FADN data.

Overall, our results reveal potential synergies and trade-offs in terms of economic and environmental performance of the identified farming systems and of switching to a more ecological farming system. In general, both identified integrated farming systems can be seen as more extensive forms of production, compared to standard farms and organic farming systems, respectively. However, the standard integrated farming system performs overall worse compared to the other groups. While this farming system performs better in terms of environmental performance compared to the standard system, it performs worse, when looking at technical economic performance. In contrast, organic and integrated organic farming systems can compete with standard farms in terms of profitability, especially, if subsidies are included. At the same time, these farming systems also perform better in terms of environmental performance than the standard system and also than the integrated system. Switching from organic to an integrated organic farming system does not lead to further economic drawbacks, while environmental performance increases clearly further.

In terms of drivers, our results show that worse site conditions, measured via the share of permanent grassland and LFA subsidies, are negatively related to efficiency in particular for the more intensive standard and organic farming systems. RD subsidies (not including LFA subsidies) only show a negative effect on efficiency for standard and integrated organic farming systems. An overall effect is that a higher specialisation, proxied by the share of dairy cows from total LSU increases efficiency.

Based on these findings we can draw the following conclusions in terms of policy recommendations: Our results indicate that adoption of the identified farming systems is strongly related to site conditions (only a small number of farms remained for matching, when controlling for site conditions and time), which cannot be influenced by policies. Consequently, the economic viability of more ecological farming systems depends also on public payments, compensating farms for natural disadvantages and the provision of public goods. However, in Austria these latter non-market outputs of ecological farming systems are also an asset, reflected in higher market prices and generally high consumer demand. Establishing markets for ecological products can thus reduce the dependency on public support and can be a further incentive for more conventional farms to switch to a more ecological farming system.

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4.4 Integrating a crop diversity index to eco-efficiency measurement for cropland farms in Sweden (SLU)

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4.4.1 Introduction

There is an agreement that higher crop diversity contributes to increasing the productivity of ecosystems and that it is therefore beneficial for sustainable crop production (Cardinale et al. 2012). This is broadly acknowledged in the ecological perspective for “sampling effect” and “complementarity effect”. Sampling effect means that growing more diverse crop species will increase the probability of growing the best-adapted species, for example, different crop species have different root systems and therefore improve the efficiency in soil nutrient up taking (Tilman, Polasky and Lehman 2005; Clark and Tilman 2017). Complementarity effect can be interpreted as crop diversity can facilitate the management of different crop species planted by using the different characteristics (Loreau and Hector 2001), for example, different crops require different management and therefore production inputs such as labour and technical factors are optimised. Furthermore, crop diversity supports farm resilience by diversifying the biological risk in farms; in this way pests and diseases are easier to control because different planting seasoning. Crop diversity can also enhance the farm ability for maintain the production under climate change (Di Falco and Chavas 2008; Di Falco and Chavas 2006). However, earlier research has also shown that changes in crop diversification can decrease the income (e.g. Louhichi et al., 2017; Cimino et al., 2015; Cortignani and Dono, 2015). The effects of crop diversity in crop production described above motivate us to incorporate a measure of crop diversity to the measurement of the Eco-efficiency for cropland farms.

Eco-efficiency accounts two dimensions of sustainability: the economic performance and ecological performance, which lead to heating empirical analysis in recent decade. The first formal definition of eco-efficiency was defined by the World Business Council for Sustainable Development (WBCSD) in the beginning of the 1990s (WBCSD, 1992) as the ratio of reduced environmental impact in relation to increased value of production. Following this research thread, the idea of eco-efficiency has been applied in measuring the relationship between economy and environment, in terms of eco-efficiency of different production units (e.g. public sectors, firms and household). Environmental impact, environmental pressure, or environmentally detrimental inputs and bad outputs such as pollution are treated as either inputs or outputs into the production process (Pittman 1983; Reinhard, Lovell and Thijssen 2002; Färe et al. 2005; Färe et al. 2008; Huang, Bruemmer and Huntsinger 2016; Beltrán-Esteve, Reig-Martínez and Estruch-Guitart 2017; Tsionas 2020). One type of eco-efficiency is measured as production value per unit of environmental impact, or as the environmental impact per unit of production value. For example, eco-efficiency equals the ratio of economic value added to environmental pressure (Picazo-Tadeo, Beltrán-Esteve and Gómez-Limón 2012) or environmental damage (Kuosmanen and Kortelainen 2005). Another type of eco-efficiency is defined as the weighted average of production efficiency, waste water efficiency and waste gas treatment efficiency (Shao, Yu and Feng 2019). Overall, eco-efficiency is used to express the ability to maximize the relationship between economic value added and environmental pressure (Huppes and Ishikawa 2005; Hoang 2011). In this paper we define the eco-efficiency (ECO-E) as ecologically adjusted production efficiency by incorporating the dynamic crop diversity variables into the production function using directional distance function.

The directional distance function approach to efficiency measurement was first proposed by Chung et al. (1997) and Chambers et al. (1998) based on Shephard (1970). It has gained popularity over the recent decades (Färe et al. 2005; Färe and Karagiannis 2013; Ma et al. 2014; Tang et al. 2016). The directional distance function allows for directional efficiency measurement, i.e., the researcher is not limited to the commonly employed efficiency concept of simultaneous proportional reductions in inputs or expansion of outputs. The advantages of the directional distance function are the parametric structure that allows derivatives of relative shadow prices of nonmarket goods and elasticities of complementary or substitutionary relationships among outputs (Blackorby and Russell 1989; Morrison Paul and Nehring 2005; Serra, Lansink and Stefanou 2011; Huang and Bruemmer 2017).

We incorporate the crop diversity index lagged by two years (CDI_{t-2}) as an input and an index of crop diversity loss in current year the Herfindahl index (HI), as an undesirable output to the production function. In other words, the HI is treated as a by-product in the production function. The novel framework applied in this paper implies measuring the ECO-E by incorporating the dynamic effects of crop diversity to the production function. Most previous studies have neglected the relevant dynamic implications of crop diversity on productivity, although Cardinale, Ives and Inchausti (2004) explained the effect of crop diversity on productivity as *"dynamic",* and *"growing stronger through successional time"*. Crop diversity has been found positively related with the production both in current and in lagged effects (Di Falco and Chavas 2008).

An unbalanced panel of data for 209 farms covering 937 observations from the Swedish Farm Accounting Data Network (FADN) database for the period 2009-2016 is used. We also analyse the ECO-E over the region and crop rotations. Integrating dynamic effects of CDI into ECO-E is expected to lead to an improved understanding of the relationship between ecological performance and production revenue, and thus the research can be instructive for adjustments in policy interventions aimed at enhancement of farmers livelihood and environment protection.

4.4.2 Theoretical background: dynamic effects of crop diversity in crop production

Crop diversity stabilised its crucial role in agricultural production, with higher crop diversity improving the crop production; in particular the productive value of biodiversity that crop diversity increases crop yields has been emphasised (Bareille and Letort 2018). Crop diversity has a production value which functions as production factors on the system, instead of external determinants (Chavas and Falco 2012). We depart from the assumption that crop diversity can be considered to contribute to the production dynamically as both input and output, and that the analysis would be biased if we considered crop diversity only as input or output in the production function. In this paper we assume the crop diversity plays its dynamic role as input and output in the production process using two assumptions: 1: crop diversity in previous years contributes to the production process as an input, and 2: crop diversity is a by-product of crop production; this means crop diversity contributes to the production process as an output. A similar assumption of the dynamic role of crop diversity has been discussed in a dynamic acreage farm-level model (Bareille and Letort 2018), where they proposed that farmers manage their crop diversity as productive capital.

We posit that crop diversity in previous years function as a production factor in the current year (assumption 1). Let us assume that the farmer use a nonnegative vector of inputs $x = (x_1, x_2, \dots, x_N) \in R_+^N$ to produce a nonnegative vector of outputs $y = (y_1, y_2, \dots, y_M) \in R_+^M$, then the production technology is denoted by $GR = \{(y, x): x\ can\ produce\ y\}$. Assuming the input set of production technology is $L(y)$, $L(y) = \{x: (y, x) \in GR\}$, then input sets $L(y)$ satisfy the properties of nonnegative, closed set, finite, weak monotonicity, and strong monotonicity when necessary (Kumbhakar and Lovell 2000). Theoretically, crop diversity satisfies the properties of input. Empirically, crop diversity has been treated as an input in the literature. In this respect, Smale et al. (1998) found the number of crop species to be associated with higher yield by analysing the relationships between crop diversity and wheat production in Pakistan. Di Falco and Perrings (2005) found a positive relationship between crop diversity and agricultural production studying on cereal production in Italy. Di Falco and Chavas (2006) treated the genetic diversity as an input in the production technology and found that crop genetic diversity could increase farm productivity and reduce risk exposure. This relates to our first assumption. Bareille and Letort (2018) considered the productive capacity of crop biodiversity as a quasi-fixed input in their acreage farm level model.

We posit that crop diversity contributes to crop production process as an output in the assumption 2. Let us assume the output sets of production technology $P(x) = \{y: (y, x) \in GR$, then the nonnegative, closed, bounded output sets $P(x)$ would satisfy the strong, or free, disposability of inputs and outputs, and a convexity property (Kumbhakar and Knox Lovell, 2000). Theoretically, crop diversity does not conflict the properties. As "reverse output" of crop diversity in the production function, we use HI as undesirable output because the magnitude had an opposite effect to the good output of crop diversity, which is consistent with literature (Lewis and Sexton 2004). Theoretically, HI meets the regularity conditions[21] of undesirable output. Empirically, HI is an ecological index for expressing a monoculture, which makes it reasonable to introduce HI as undesirable byproduct from crop production in arable land.

4.4.3 Data and model specification

4.4.3.1 Data

The empirical data used here is an unbalanced panel of data for 209 individual farms and a total of 937 observations of cropland farms (specialist cereals, oilseeds and protein crops, general field cropping, and mixed cropping) obtained from the Swedish farm accounting data network (FADN) for the period 2009-2016[22] (Table 1). The economic output (y) is the total revenue of agricultural products from the arable land, measured in Swedish Kronor (SEK). The classic economic inputs of the production function are: arable land area size (x_1), in ha; labour (x_2), in working hours per year; fixed cost (x_3), measuring fixed asset input in the agricultural production, in SEK; intermediate cost (x_4), representing the variable cost excluding the cost for chemical inputs i.e. fertiliser and pesticide, in SEK; and cost of chemicals (x_5) in SEK. All variables represent the economic output and the inputs for the production function were calculated based on standard FADN definitions (European Commission, 2018). The arable land for agricultural production is located mainly in the South and North Sweden, thus we use the arable land located in the South and North with region code 710 and 730 in FADN database.

In addition to the economic variables of the production function, we use the HI (b) (Malik and Singh 2002) in current year as a bad output, and the CDI in the past two years (t-2) (x_6) as an input for the

[21] For modeling technology producing undesirable by-products, two axioms of null-jointness and weak disposability are required for the output (Färe et al. 1997, 2005; Huang et al., 2018). Null-jointness means that good output can only be produced if some undesirable output is produced, that can be interpreted that no undesirable output produced means no good output produced. Weak disposability requires that simultaneous reduction of good output and undesirable output is feasible, which means there is cost to reduce production of undesirable output.

[22] The crop diversity index in the past two years was calculated using data from 2007 to 2014.

production function w.r.t. the ecological side. The HI is defined as $HI = \sum_{i=1}^{n} P_i^2$, where P_i is the proportion of area planted by the crop i: $P_i = \frac{A_i}{\sum_{i=1}^{n} A_i}$, A_i is the area of the crop i, i is each of the crops such as ley, barley, wheat, oat etc. HI was used as a spatial diversity by Smale et al. (2008) in wheat production, where spatial diversity refers to the area distribution of varieties. A HI value of 1 indicates that the farm planted a single crop i.e. a monoculture, while a value of 0 indicates that a large number of crop varieties were planted in the farm i.e. multiculture. CDI is defined as $CDI = 1 - HI$. The CDI is directly related to the diversification in the farm by taking into account the area devoted to each crop, and ranges between 0 and 1, the greater the number of CDI, the higher degree of crop diversification. Whereas, the greater the number of HI, the higher the degree of monoculture in the arable land. As we explained in assumption 1, the crop diversity of the previous year is expected to increase the current production (Di Falco and Chavas, 2008); that led us to apply the crop diversity in previous two years (CDI_{t-2}) as an input in the production function. We applied a robustness test to see how many years lagged in previous years can affect the production most significantly, and we get the lagged year of 2 is the most significant statistically. The mean of CDI_{t-2} and CDI in current year were 0.79 with a standard deviation (Std. Dev.) as 0.18.

Table 1: Descriptive statistics of variables

Variable Description	Symbol	Unit	Mean	Std. Dev.
Continuous variables				
Cropland area	x_1	ha	109.93	105.2
Labour	x_2	working hours	2927.86	3083.95
Fixed cost	x_3	1000 SEK	769	1440
Intermediate cost without chemicals (fertiliser and pesticides)	x_4	1000 SEK	192	3380
Cost of chemicals (fertiliser and pesticide)	x_5	1000 SEK	421	570
CDI two years before, CDI_{t-2}	x_6	-	0.801	0.19
Total revenue of agricultural outputs	y	1000 SEK	2260	3450
CDI in current year		-	0.79	0.21
HI	b	-	0.21	0.79
Dummy variables			Obs. no. of 1	Obs. no. of 0
Main crop change (1 = at least the main crop has been changed in past years, 0 = otherwise)		d_1	262	675
Year dummy of policy shock (1 = year later than 2013, 0 = otherwise)		d_2	672	265

For the environmental side, we have also included a dummy variable of main crop change (d_1) and a year dummy of policy shock (d_2). Main crop means the largest planted area of a single crop for each observation in the sample. The dummy variable of main crop change equals to 1 means at least the main crop has been changed in past years, it equals to 0 otherwise. The year dummy of policy shock is set to be 2014, that means the year dummy equals to be 1 for cropping after 2014, and 0 otherwise. The crop diversification measure was introduced by the 2013 Common Agricultural Policy (CAP) reform as part of CAP "greening" (crop diversification together with maintenance of permanent pasture, ecological focus areas) (European Union, 2013). The measure was targeted to land allocation at farm level, with the aim to enhance the ecological performance of the EU agricultural sector, and to generate environmental public goods to the society. Arable, monoculture farms were the implicit target of the reform. To comply with this measure, farmers had to delimit the proportion of the main crop. Non-

compliance with the measure implied restriction in direct payments (30% of the farmers' direct payments are conditional on the "greening").
Crop rotation is alternating annual crops grown on a specific field in a planned pattern or sequence in successive crop years for risk diversification in the farm. The crop rotation can take the advantage of different root systems of crops to improve soil nutrients taking and improve the soil quality. However, because we cannot identify the land parcel of a specific crop on an individual farm from the FADN database, we instead investigate the main crop change to reflect the practice of crop rotations. Comparing the planting area of crops, the first three main crop types in Sweden are ley (45%), wheat (20%), and corn (18%). Thus, grass for ley takes the largest area in more than half farms, followed by barley and wheat. We generated a dummy variable of whether the largest planted crop area changes in each farm, and we found 262 farms changed the first main crop at least once from 2009 to 2016, we assumed this is also an indicator of crop rotation.

4.4.3.2 Model *specification*

Following Chambers et al. (1998; 2002) and Färe et al. (2005), we first build the output oriented directional distance function. The advantage of the output oriented directional distance function is that it allows us to expand the desirable output of agricultural revenue while contracting the undesirable output HI holding inputs unchanged, as shown in Figure 1. Assuming point A is the production point of a farm, then the farmer improves production along the directional vector $g = (g_y, -g_b)$, that is adding ϑg_y to desirable output while subtracting ϑg_b from the undesirable output. The directional distance function is shown as equation (1):

$$\overrightarrow{D_o}(x, y, b; g_y, -g_b) = sup\{\vartheta: (y + \vartheta g_y, b - \vartheta g_b) \in P\} \tag{1}$$

while satisfying the translation property, it can be denoted as equation (2):

$$\overrightarrow{D_o}(x, y, b; g_y, -g_b) - \vartheta = \overrightarrow{D_o}(x, y + \vartheta g_y, b - \vartheta g_b; g_y, -g_b) \tag{2}$$

We parametrically estimate the directional distance using stochastic estimation methods following Kumbhakar and Lovell (2000), when $\overrightarrow{D_o}(x, y, b; g_y, -g_b)$ is assumed to be 0 and error term $\varepsilon_i = v_i - u_i$ is added, then empirical stochastic specification form based on equation (2) is written in equation (3) after fulfilling the translation property and symmetry condition, and assuming $g = (g_y, -g_b) = (1, -1)$. In our case, we impose these restrictions by choosing $\vartheta_i = b_i$, then the quadratic form of the empirical specification for ECO-E measurement is below:

$$\begin{aligned}
&\overrightarrow{D_o}(x, \mathrm{y}, b; 1, -1) \\
&\qquad = \alpha_0 + \sum_{k=1}^{6} \alpha_k x_k + \beta_1 y + \gamma_1 b + \frac{1}{2}\sum_{k=1}^{6} \alpha_{kk}(x_k)^2 + \frac{1}{2}\beta_2(\mathrm{y})^2 + \frac{1}{2}\gamma_2(\mathrm{b})^2 \\
&\qquad + \sum_{k=1}^{6} v_k\, x_k \mathrm{b} + \mu\mathrm{yb} + \sum_{k=1}^{6} \delta_k\, x_k \mathrm{y}
\end{aligned} \tag{3}$$

$$\begin{aligned}
-b_i &= \overrightarrow{D_o}(x, {y_i}^*, 0) + v_i - u_i \\
&= \alpha_0 + \sum_{k=1}^{6} \alpha_k x_k + \beta_1 y + \gamma_1 b + \frac{1}{2}\sum_{k=1}^{6} \alpha_{kk}(x_k)^2 + \frac{1}{2}\beta_{11}(\mathrm{y})^2 \\
&+ \sum_{k=1}^{4} \sum_{l=1, k\neq l}^{4} \alpha_{kl} x_k x_l + \sum_{k=1}^{4} \gamma_{k1}\, x_k y^* + v_i - u_i
\end{aligned}$$

Where in, $y_i^* = y_i + b_i$, y_i describes the desirable output of agricultural products revenue, b_i denotes the undesirable output HI. Inputs x_k represent x_1 (arable land area), x_2 (labour), x_3 (fixed cost), x_4 (intermediate cost excluding the cost chemicals (i.e. pesticide and fertiliser)), x_5 (cost of chemicals), and x_6 (CDI two years ago (CDI_{t-2})). v_i is a random error term, intended to capture events beyond the control of the farmers and u_i is a non-negative random error term, intended to capture production inefficiency.

Based on duality between the distance function and cost or revenue function (input distance function for cost minimisation function, output distance function for revenue maximisation function), relative shadow prices for HI can be derived (Shephard 1970; Färe and Primont 1996).

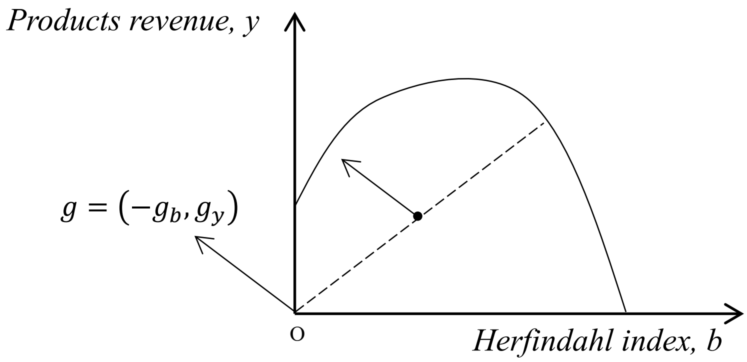

Figure 1: Directional distance function framework

4.4.4 Results and discussion

Before presenting the results from the directional distance function, we used likelihood ratio tests for evaluating model performance, all tests confirm that the current model setting is appropriate for our data.

4.4.4.1 Parameter estimates and elasticity of eco-efficiency to inputs

The directional distance function using maximum likelihood is presented in Table 3, with all variables divided by mean. Most coefficients are statistically significant. The directional output distance function is concave in outputs, thus $\partial^2(\overrightarrow{D_o}(x, y, b; 1, -1))/\partial y^2 = \beta_{11} \leq 0$, and according to the restrictions implied by the translation property, $\partial^2(\overrightarrow{D_o}(x, y, b; 1, -1))/\partial b^2 = \partial^2(\overrightarrow{D_o}(x, y, b; 1, -1))/\partial y \partial b = \beta_{11}$, where β_{11} is estimated to be -0.050 (p-val < 0.01). The first order coefficient of CDI two years lagged (x_6) is estimated to be -0.134 (p-val <0.1). The second order coefficient of CDI_{t-2} (x_6) is estimated to be 0.170 (p-val < 0.05). As the dependent variable in the directional distance function is $\overrightarrow{D_o}(x, y, b; 1, -1)$, this means that there is a reverse U shape relationship between the ECO-E and CDI two years ago (x_6).

Table 2: Estimates of directional distance function

Variables	Symbol	Coef.	Std. Err.	Variables	Coef	Std. Err
Dependent variable: $\vec{D}(x, y, b;\ 1, -1)$						
x_1		-0.033*	0.020	$x_1 \cdot x_2$	-0.034***	0.008
x_2		0.080*	0.046	$x_1 \cdot x_3$	0.064***	0.007
x_3		-0.296***	0.043	$x_1 \cdot x_4$	-0.076***	0.009
x_4		1.001***	0.047	$x_1 \cdot x_5$	-0.015***	0.004
x_5		0.068***	0.017	$x_1 \cdot x_6$	0.026	0.018
x_6		-0.134*	0.071	$x_2 \cdot x_3$	-0.014*	0.008
y		-0.926***	0.016	$x_2 \cdot x_4$	-0.011	0.011
b		0.074		$x_2 \cdot x_5$	-0.005	0.004
$0.5 \cdot (x_1)^2$		-0.003***	0.001	$x_2 \cdot x_6$	0.001	0.039
$0.5 \cdot (x_2)^2$		-0.003	0.014	$x_3 \cdot x_4$	-0.019**	0.009
$0.5 \cdot (x_3)^2$		0.008	0.009	$x_3 \cdot x_5$	0.001	0.003
$0.5 \cdot (x_4)^2$		-0.120***	0.016	$x_3 \cdot x_6$	0.132***	0.033
$0.5 \cdot (x_5)^2$		-0.000	0.001	$x_4 \cdot x_5$	-0.004	0.004
$0.5 \cdot (x_6)^2$		0.170**	0.077	$x_4 \cdot x_6$	-0.149***	0.037
$0.5 \cdot (y)^2$, $0.5 \cdot (b)^2$, $y \cdot b$		-0.050***	0.004	$x_5 \cdot x_6$	-0.025*	0.014
$x_1 \cdot y$, $x_1 \cdot b$		0.000***	0.000	*Dummy of crop rotation*	-0.016***	0.005
$x_2 \cdot y$, $x_2 \cdot b$		0.000***	0.000	*Dummy of year 2014*	-0.011**	0.005
$x_3 \cdot y$, $x_3 \cdot b$		0.000***	0.000			
$x_4 \cdot y$, $x_4 \cdot b$		0.000***	0.000			
$x_5 \cdot y$, $x_5 \cdot b$		0.000	0.000			
$x_6 \cdot y$, $x_6 \cdot b$		0.022*	0.012			
Statistics						
equation of σ_u						
Constant		-3.314***	0.071			
Constant		-5.195***	0.119			
σ_u		0.074	0.004			
λ		2.561	0.011			
Log likelihood=1738.882				LR test of sigma_u=0: chibar2(01) = 82.34		

*Significant at 10% level (P < 0.10), **Significant at 5% level (P < 0.05), ***Significant at 1% level (P < 0.01)

Based on the estimates from the directional distance function, the elasticities of the eco-inefficiency with respect to (w.r.t.) inputs and outputs are calculated to get a more complete understanding of the production performance. The value of $\overrightarrow{D_o}(x, y, b; 1, -1)$ indicates the level of eco-inefficiency; thus $\partial(\overrightarrow{D_o}(x, y, b; 1, -1))/\partial x$ measures the elasticity of eco-inefficiency w.r.t. inputs (Table 4). The elasticity of eco-inefficiency w.r.t. land area size (x_1) and fixed cost (x_3) are found negative, as shown in Table 4, which implies that there are positive relationships between ECO-E and these two inputs, suggesting that increasing the inputs farmland and fixed cost will increase potential higher ECO-E. Does this also mean the larger farms have higher ECO-E potential? The literature has pointed to arguments that small scale farms have higher ECO-E in agricultural production (Zhong et al. 2020; Stępień et al., 2021). There is also the argument that small and labour-intensive farms are associated with a higher degree of ECO-

E compared to capital-intensive farms (Grzelak et al. 2019). In light of our finding of the relationship between farmland size and ECO-E, we suggest that the EU CAP should consider multiple factors related to ECO-E instead of applying one-size-fits-all policy. The elasticity of eco-inefficiency w.r.t. labour (x_2), intermediate cost without chemicals (x_4), cost of chemicals (x_5) and CDI two years lagged (x_6) are found to be positive, which means there are negative relationships between these inputs and ECO-E. The largest elasticity of the eco-inefficiency w.r.t. inputs is associated with the intermediate cost without chemicals (x_4), estimated at 0.640 at the sample mean. This implies that greater intermediate cost excluding chemicals (x_4) would be correlated with higher eco-inefficiency. The elasticity of eco-inefficiency w.r.t. CDI_{t-2} (x_6) is estimated at 0.063 at the sample mean, implying a 1% decrease of CDI_{t-2} would decrease the potential ECO-E by 6.3% on average. According to the finding of Di Falco and Chavas (2008), crop diversity is positively related with production in lagged effects, which indicates that maintaining a diverse crop pattern would enhance agricultural productivity in the long run. However, our result is not consistent with the previous research, where the positive effect of crop diversity becomes stronger by time (Cardinale et al., 2004; Di Falco and Chavas, 2008).

Table 3. Elasticity of eco-inefficiency w.r.t. inputs

Variable	Mean	Std. Dev.	Min	Max
ε_{x1}	-0.067	0.050	-0.779	0.094
ε_{x2}	0.019	0.058	-0.624	0.078
ε_{x3}	-0.125	0.081	-0.516	1.103
ε_{x4}	0.640	0.220	-1.588	0.984
ε_{x5}	0.022	0.020	-0.270	0.067
ε_{x6}	0.063	0.079	-0.806	0.860

The production function includes two additional dummy variables; one considering whether the main crop is changed during the observed period and one considering whether the year is later than 2013. The dummy variable of crop rotation was estimated to be -0.016 (p-val < 0.01), indicating that the crop rotation would significantly improve the ECO-E. Empirically, Crop rotations can substantially increase the soil organics, such as biomass C and N pools, and therefore benefit the production (McDaniel et al. 2014). The dummy of year 2014 is also estimated to be significantly as -0.011 (p-val < 0.05), which means the farms are more eco-efficient after 2013. We interpret this as relating to the CAP reform in 2013, and the mandatory greening component of the direct payments was introduced to promote sustainable land use.

4.4.4.2 Analysis of ECO-E scores

The average estimated ECO-E is 0.876 (Table 4), which indicates that on average, cropland farmers can improve ECO-E by 12.4% in terms of expanding agricultural products revenue and reducing HI given unchanged inputs. In Figure 2, we can see the histogram distribution of ECO-E, where there is an overall histogram distribution in the up-left position, the histogram distribution by Southern Sweden and Northern Sweden seem also satisfactory. The average ECO-E in Southern Sweden is 0.875, while the average ECO-E in Northern Sweden is 0.879. Although there is no significant regional difference between the average ECO-E in Southern and Northern Sweden, the minimum ECO-E in Southern Sweden (0.273) is much lower than the minimum ECO-E in Northern Sweden (0.609). This is expected because farming in Southern Sweden is comparatively more intensive, more fertiliser and pesticide are used in agricultural production, which therefore leads to less environmentally friendly production and a lower ECO-E in Southern Sweden. Summaries of ECO-E by farming type are also interesting. The ECO-E for conventional farming, organic certificated farming, and mixed or transitional organic farming are

0.876, 0.886, and 0.845 respectively. Although there is no significant difference between the average ECO-E for conventional farming, organic certificated farming, and mixed or transitional organic farming, the minimum ECO-E for certificated organic farming is highest among the three types of farming that is 0.684.

Table 4: Summary of eco-efficiency (ECO-E)

ECO-E	Obs	Mean	Std. Dev.	Min.	Max.
Overall ECO-E	937	0.876	0.082	0.273	0.990
Summary by regional location					
ECO-E in southern Sweden	871	0.875	0.083	0.273	0.990
ECO-E in northern Sweden	66	0.879	0.061	0.609	0.975
Summary by farming type					
ECO-E for conventional farming	861	0.876	0.082	0.273	0.990
ECO-E for certificated organic farming	56	0.886	0.058	0.684	0.973
ECO-E for mixed or transitional organic farming	20	0.845	0.130	0.455	0.962

4.4.5 Conclusion

Sustainable agriculture seeks to increase the production of high-quality food and fibres to meet current social and economic requirements while simultaneously maintaining healthy ecosystems to support the productive and economic needs of future societies. Transforming agriculture to be more in line with sustainability requires us to take economic, environmental, and societal performance into account. Analysis of ECO-E of farms improves our understanding about possible synergies or trade-offs between economic performance and ecological performance as agriculture become more in line with sustainability. Loss of biodiversity is one of the most significant sustainability problems in Swedish agriculture (Morberg et al., 2020). Crop diversity improves the cultivated biodiversity with impacts both below and above ground. The novelty of this paper is that it measures ECO-E in cropland farms by incorporating the dynamic effects of crop diversity into the production function when assessing ECO-E. The innovation of the approach lies in that the dynamic effect of crop diversity is addressed in ECO-E measurement, by treating the lagged crop diversity as one input, and the crop diversity loss in current year as an undesirable output. In the empirical modelling, the output of crop diversity loss is represented by the "reverse output" in the directional distance function. Aside of the ecological input and output, we account for land, labour, fixed cost and variable cost as inputs and revenue for agricultural product as normal good output for the production in cropland in Sweden.

The average ECO-E is estimated to be 0.873, although the average ECO-E in Northern Sweden is slightly higher than that in the Southern Sweden, the minimum ECO-E in Northern Sweden is much higher than the minimum ECO-E in Southern Sweden. CDI_{t-2} is estimated to positively contribute to ECO-E of crop production significantly.

Our results show that the crop diversification is a burden on the farm economy, and is related to the regional economic and environmental characteristics. The new CAP 2021-2027 is aiming at better targeting for securing stable economic incomes and intensifying the environmental and climate actions, with increased focus on biodiversity (European Commission, 2021). Given our results, to achieve the goals, policy compensation schemes should take into consideration the income forgone, given the regional potential, both in terms of agricultural production and environmental endowments.

While this paper introduces a novel approach to considering crop diversity in the ECO-E measurement of cropland farms, several interesting avenues for future research in this area remains. First, the unbalanced panel data used will hide interesting information between panels, for example, the group effects of crop species in terms of ECO-E, and future research will have an important role to effects of crop species between panels. Second, by gathering information about the positioning of specific crop plots the measurement of crop rotation and crop diversity can be improved. This would enable assessment of even more precise ecological effects of production and to further refine the analysis of synergies and tradeoffs between ecological and economic effects. Third, crop diversity is only one component part of the total biodiversity of an ecosystem. Future research could use the approach we developed here to expand the biodiversity consideration in the ECO-E measurement by also considering wild species, for instance by considering use of seminatural pasture areas, wild flower strips between fields etc. In this respect, the approach introduced here is promising to even better understand the tradeoffs and synergies between farms contribution to biodiversity and economic values.

4.4.6 References

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4.5 Estimating eco-efficiency of the olive farms in Crete, Greece (DEMETER)

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4.5.1 Introduction and description of case study region

Eco-efficiency is defined as the "efficiency with which ecological resources are used to meet human needs" (OECD, 1998) and it expresses the ability of a production unit to achieve economic results with the minimum possible use of resources and environmental impact (see also Ehrenfeld, 2005). Therefore, eco-efficiency is often used to measure the economic and environmental performance of a production unit.

Agriculture is an economic activity that depends highly on the use of natural resources and interacts closely with the surrounding ecosystem. Some of the main environmental impacts associated with agriculture are soil degradation, biodiversity loss, natural resources overuse, water and soil pollution from the use of agricultural inputs and emission of greenhouse gases (Gołaś at al., 2020; Gołębiewska and Pajewski, 2018). The concept of eco-efficiency is particularly relevant when it comes to evaluating the performance of farming activities and has gained attention as a way to achieve sustainability of the food supply chain (Gołaś et al., 2020).

Indeed, the pursuit of sustainable food production systems and dietary patterns is promoted worldwide and is targeted by agricultural policies. According to W.H.O. (2019), a sustainable diet promotes all dimensions of individuals' health and wellbeing, has low environmental pressure and impact, is accessible, affordable, safe and equitable, and is culturally acceptable. The Farm to Fork Strategy[23] encourages consumers to switch to more sustainable diets and producers to adopt environmentally friendly farming practices. Within this context, the Mediterranean diet, the cultural and health value of which has already been acknowledged (UNESCO, 2013) is viewed as an alternative sustainable diet, provoking the research interest in its environmental aspects. Olive consumption is a fundamental element of the Mediterranean diet, and its benefits on health are numerous and well documented (Covas et al., 2006; Uylaşer and Yildiz, 2014; Gorzynik-Debicka et al., 2018). On the production side, olive cultivation is an important agricultural activity for the Mediterranean basin and offers income to many families in the area, as it is commonly included in the portfolio of Mediterranean farms.

On the other hand, as any other agricultural activity, olive oil production is associated with environmental concerns like soil degradation and water and input (fuel, pesticides and fertilisers) overuse (Banias et al., 2017). Since olive oil is promoted as part of a sustainable diet, light needs to be shed on the production practices that minimize any adverse effects on the environment and the pathways to agroecological transition of olive cultivation.

This study aims to address the issue of eco-efficiency of olive farms in Crete, Greece, considering their main cultivation practices, across agroecological farm types. In Greece, a total of 792,642.5 ha of olive groves are kept, with the Prefectures of Peloponnese and Crete accounting for 27% and 23% of the total cultivated area, respectively (HAS[24], 2017). The total number of trees cultivated in Greece in 2017

[23] Available at: https://ec.europa.eu/food/sites/food/files/safety/docs/f2f_action-plan_2020_strategy-info_en.pdf
[24] Hellenic Statistical Authority

was 148,053,557 which corresponds to an average density of 187 trees per hectare. The total olive production of the country reached 311,727 tons in 2017.

This analysis focuses on the Prefectures of Heraklion and Lasithi, located in the eastern part of the island, where 89,644.6 and 27,086.4 ha of olive groves are kept, respectively (HAS, 2017). This area corresponds to 15% of the total olive trees of the country and 17% of the total olive production. The number of olive farms located in the area under investigation was 52,707 in 2016, which accounts for 12% of the total Greek olive farms (HAS, 2016). Olive production is a well-established activity in Crete due to the existing climatic conditions and the ability of the olive trees to adopt to drought and salinity (see for example Vasilaki et al., 2008).

It is also important to emphasize that organic olive cultivation refers to 3% of the total olive cultivation in the study area, which corresponds to 3,721 ha and 1,016 farms (Tzouramani et al., 2019). AGRO 2, which is a quality certification for the Integrated Management System, is also common in the area under investigation (Duvaleix et al., 2020). The number of AGRO 2 certified farms was 2,508 in Heraklion and 2,658 in Lasithi, which corresponds to 6,623 ha and 5,422 ha, respectively (Duvaleix et al., 2020).

One of the main challenges regarding eco-efficiency and in general environmental performance is its estimation with a single aggregate indicator, as will be further discussed in our analysis (Russo et al., 2016; Gołaś et al., 2020). In this study we employ the Data Envelopment Analysis (DEA) for this purpose. DEA has been widely used in agricultural economics as a method to estimate the traditional technical efficiency of farms (Lansink and Reinhard, 2004; Theodoridis et al., 2006; Zhu and Demeter, 2012; Latruffe et al., 2017; Madau et al., 2017). Many studies in Greece and abroad also use the analysis to estimate the technical and economic efficiency of olive farms (Lachaal et al., 2005; Lambarraa et al., 2007; Kashiwagi at al., 2012; Beltrán-Esteve, 2013; Bernal-Jurado et al., 2017; Niavis et al., 2018; Stilitano et al., 2019; Raimondo et al., 2021). The DEA methodology has also been used as a method to estimate eco-efficiency of agricultural activities, since it holds many advantages (see for example Picazo-Tadeo et al., 2011; Ullah et al. 2016; Coluccia et al., 2020; Eder et al., 2021).

In our case study we follow the work of Gómez-Limón et al. (2012), who estimate eco-efficiency of olive farms in Andalucía, by implementing the methodology described by Kuosmanen and Kortelainen (2005) and using various indicators to estimate environmental burdens. Farm and farmer characteristics that determine eco-efficiency are also investigated by implementing regression analysis (see for example: Urdiales et al., 2016). Eco-efficiency of the olive farms is examined across different agroecological farm types, identified within the LIFT project.

4.5.2 Data

The data used for the estimation of eco-efficiency of the Cretan farms is part of the LIFT large-scale farmer survey dataset. The data gathered in Greece refers to both olive and vineyard farms, but for the purpose of this case study, specialist olive farms were selected. We consider a farm as specialist olive when two thirds of the farm output (revenues) come from olives (mainly oil production)[25]. Following this rule 73 out of the 108 farms of the Greek sample are characterised as specialist olives. This group of farms was then checked for outliers, since the DEA methodology that was performed is sen-

[25] This rule is in line with the typology of farms in FADN according with their Standard Gross Margin (SGM) (https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:31985D0377&from=EN. In our analysis we use the value of output instead of the SGM since the specific costs considered in the latter cannot be broken down to the activities of the farm. Thus, we assume that these costs would be proportional to the revenues of each activity.

sitive to outliers. Eight farms were excluded from the final sample as important information like revenues was missing (incomplete interviews). The remaining 65 farms that were considered in the analysis have an average size of 4.9 hectares which yield on average 13,340€ of output (excluding subsidies) and correspond to 2,175 hours of labour (1.24 FTE[26]).

The specialist olive farms were almost equally distributed between the two case study areas, since 32 are located in Heraklion and 33 in Lasithi. Their land is located in low altitudes, less than 600m, while 30 of the farms report their farmland to be located in an altitude less than 300m. The majority of land is also irrigated (57 farms).

Regarding their agroecological profile, 27 are organic, 44 fall into the conservation farms category, 5 are considered low input, 5 are integrated and 5 are characterised as medium input, according to the LIFT survey based protocol for farm typology, developed within the LIFT project (Rega et al., 2021). The farm owners are in their majority male (52) and their average age is 53 years. They are considered experienced farmers since their average years of experience in agriculture are 31. Twenty-seven of them have higher education and 33 have finished either middle school or high school. It should also be mentioned that 14 of them have agricultural education provided either at high school or at the university level. The labour inputs mainly derive from the farm household, since 75% of the total labour comes from the family members. On average 1.1 members of the family offer their employment in the olive farms. The farms also occupy on average 2.89 hired workers, mainly seasonal, who perform tasks like harvesting of olives or pruning of the olive trees.

Regarding the managerial profile of the olive farms, it should be emphasised that even though they specialize in olive production, pluriactivity is common since on average, only one third of the household income comes from agriculture. Furthermore, it is important to mention that the farmers of our sample seem to place more emphasis on health and environmental objectives. Specifically, when asked to evaluate a set of objectives, during the LIFT large scale farmer survey, “Being fit and healthy”, “Protecting the environment for future generations” “farming in a way that enhances the environment”, “Producing high quality products” and “improving the condition of land” received the highest scores on a 5-point Likert scale (4.41, 4.40, 4.35, 4,32 and 4.27, mean value respectively). On the other hand, economic objectives like “Expanding the business”, “Maximising profit”, “Maximising production”, and “Minimising risk” received lower scores (3.49, 3.96, 4.04 and 4.07, mean value respectively).

Finally, for the olive farms of the sample, the main distribution channel is the producers’ organisations, followed by merchants and wholesalers and processors, while a very small part of the production is directly sold to consumers at an average selling price of 3.18€/kilo.

4.5.3 Methods

To estimate eco-efficiency in this study we implement the methodology proposed by Kuosmanen and Kortelainen (2005) and followed in a number of studies on agricultural activities (Picazo-Tadeo et al, 2011; Ullah et al., 2016; Urdiales et al., 2016; Godoy-Durán et al., 2017; Soliman and Djanibekov, 2020). Kuosmanen and Kortelainen (2005) employ DEA as a method to aggregate environmental pressures to construct a single eco-efficiency index. DEA is a non-parametric method to estimate efficiency, originally developed by Charnes et al (1978). The methodology is based on the construction of a production frontier where all the decision making units (DMU), or in our case farms, that use minimum level of inputs to produce a certain output lie (benchmark units). This production frontier is deterministic and every deviation from the frontier is considered as inefficiency.

[26] One Full Time Equivalent (FTE) is equal to 1,750 hours of labour.

Let N a sample of DMUs, V_n the economic value added and Z_n the environmental pressures of unit n (n=1,2,…,N). Eco-efficiency can be defined as:

$$EE_n = \frac{V_n}{D(Z_n)} \tag{1}$$

Where D is the damage function that aggregates the M environmental pressures into a single environmental damage score (Kuosmanen and Kortelainen, 2005). A linear approximation of D would be a weighted sum of all environmental pressures:

$$D(z) = w_1 z_1 + w_2 z_2 + \cdots + w_M z_M \tag{2}$$

where w_m (m=1,…,M) represents the weight of environmental pressure m. DEA can be implemented to estimate the weights that maximize the efficiency score of each production unit n as follows:

$$\max EE_n = \frac{V_n}{w_1 Z_{n1} + w_2 Z_{n2} + \cdots + w_M Z_{nM}}$$

Subject to:

$$\begin{gathered}
\frac{V_1}{w_1 Z_{11} + w_2 Z_{12} + \cdots + w_M Z_{1N}} \leq 1 \\
\frac{V_2}{w_1 Z_{21} + w_2 Z_{22} + \cdots + w_M Z_{2N}} \leq 1 \\
. \\
. \\
. \\
\frac{V_N}{w_N Z_{N1} + w_2 Z_{N2} + \cdots + w_M Z_{NN}} \leq 1 \\
w_1, w_2, \ldots., w_M \geq 0
\end{gathered} \tag{3}$$

As in the case of technical efficiency, the above constraints impose that the maximum value of eco-efficiency is one (100%) and always positive or zero (since the weights are always positive or zero). Higher values indicate good-environmental performance, whereas values closer to zero indicate higher eco-inefficiency. The above problem is not linear and requires a lot of computational effort to solve. But we can overcome this issue if the inverse of the eco-efficiency ratio is minimised as follows:

$$\min EE_n^{-1} = w_1 \frac{Z_{n1}}{V_n} + w_2 \frac{Z_{n2}}{V_n} + \cdots + w_M \frac{Z_{nM}}{V_n}$$

Subject to:

$$\begin{gathered}
w_1 \frac{Z_{11}}{V_1} + w_2 \frac{Z_{12}}{V_1} + \ldots. + w_M \frac{Z_{1M}}{V_1} \geq 1 \\
w_1 \frac{Z_{21}}{V_2} + w_2 \frac{Z_{22}}{V_2} + \ldots. + w_M \frac{Z_{2M}}{V_2} \geq 1 \\
. \\
. \\
. \\
w_1 \frac{Z_{N1}}{V_N} + w_2 \frac{Z_{N2}}{V_N} + \ldots. + w_M \frac{Z_{NM}}{V_N} \geq 1
\end{gathered} \tag{4}$$

$$w_1, w_2, \ldots., w_M \geq 0$$

It should be emphasised that the DEA eco-efficiency score indicates the maximum equiproportionate reduction in all environmental pressures that is technically possible given the level of economic activity V.

In our analysis we use four indicators that correspond to the main environmental burdens associated with olive cultivation (see also Table 1):

1. *Water consumption*. Irrigation water use is one of the main environmental concerns associated with agricultural activities. Particularly in the region of Crete, many areas of the island already face water scarcity, while drought and extreme precipitation events are expected to increase as the result of climate change (Tapoglou et al., 2019). Even though olive cultivation is not considered water demanding and is traditionally rainfed, climate change and the intensification of the activity place extra attention to water management as a way to safeguard this valuable natural resource and maintain the activity. Gómez-Limón et al (2012) also use water consumption as a variable in their eco-efficiency analysis.
2. *Fuel consumption*. Fuel consumption is considered in this analysis as an approximation of greenhouse gas emissions (GHGs) from practices carried out within the farm[27]. It should be noted that fuel is the main energy source used in the olive farms and its consumption is often very high because of the structure (multiple land plots) of Greek farms.
3. *Soil management.* This indicator was adopted from the LIFT survey-based protocol for farm typology (Deliverable 1.4, Rega et al., 2021)[28]. Specifically, the analysis uses the normalised score estimated for the characterisation of conservation farms, which in fact aggregates all the soil management practices performed in olive farms. These practices include soil tillage intensity (no tillage, conservation tillage and conventional tillage) and soil cover and fertilisation (planting of cover crops, leaving crop residues on soil, planting of catch crops, crop rotation and mixed cropping). Each of these practices, is included in the calculation of the soil management index as a binary variable that takes the value of 1 if the practice is implemented in the farm and zero otherwise. Next, the score of each variable was appointed weights that derived by taking into account expert opinions and the percentage of the farm land that the practice was implemented. For the former, experts were asked to score the practices (from 0 to 10) according to their significance. The final scores for each farming practice were thus calculated as the averages of the scores given in the four responses. For example, the scores appointed to conventional tillage, conservation tillage and no tillage were 0, 8.5 and 10 respectively. This score was then multiplied by an area weight, according to the area that the practice was implemented[29]. Lastly, the final score was calculated as a weighted sum of each criterion (e.g. tillage and soil cover) and was in turn normalised in a scale of 0 to 10, to build the soil man-

[27] The available data on inputs used in the farm-mainly fertilisers, composts, soil improvements, pesticides etc- does not allow estimations of the pre-chain GHGs that are associated with the manufacture and transportation of these inputs. Therefore, only the fuel consumed for everyday tasks performed within the farm, like cultivation, fertilisation, pruning, olive collection and pest control (see also Feliciano et al, 2014) are used as an estimation of GHGs. However, it should be emphasised that as indicated by the relevant literature fuel consumption within the farm (i.e. for the cultivation of olive trees) is far more significant than any pre-chain fuel consumption (i.e. for the production and transportation of inputs) (Tsarouchas et al., 2015). Specifically, Tsarouchas et al. (2015) estimate that the cultivation of olives is the greatest contributor to global warming in the olive oil production chain (40.37%).

[28] Rigby et al. (2001) discuss the issue of constructing farm level indicator of sustainability in more detail.

[29] These weights are 0.025 when the percent of the farm area is less than 5%, 0.15 when the area is between 5 and 25%, 0.375 when the area is between 25 and 50%, 0.625 when the area is between 50 and 75% and 0.875 when the area is between 75 and 100%.

agement composite indicator. It should be emphasised that the inverse of the soil management indicator was incorporated in the model as an environmental burden, since the score is higher when practices that enhance soil quality are implemented. Gómez-Limón et al. (2012) also incorporate relevant practices in their analysis using alternative indicators (a soil erosion indicator and a biodiversity indicator).

4. *Fertilisation and pest management.* This indicator was also built based on the LIFT survey-based protocol for farm typology (Rega et al., 2021) and was adopted from the *low input farm* type. Specifically, the practices that were considered to build this indicator refer to fertiliser use (inorganic fertiliser, animal manure, sewage sludge, compost and soil amendments) and pest control (use of chemical pesticide and products allowed in organic farming). As in the case of the previous indicator, expert opinion weights and area weights were used for the final estimation of the aggregate indicator (See Deliverable 1.4 for a more detailed description of the methodology used to weight the aforementioned practices). For our analysis, the two main criteria (fertilisation and pest control) receive equal weights. Again, the inverse of the estimated fertilisation and pest management indicator was incorporated in the model to denote environmental burden. In the study of Gómez-Limón et al. (2012), the variables *pesticide risk* and *nitrogen ratio*, used in their DEA model can be considered as the corresponding variables to our *Fertilisation and pest management* indicator.

Table 1: Definitions of the variables used in the DEA analysis.

	Definition
Environmental pressures	
Water consumption	Total amount of irrigation water used per hectare
Fuel consumption	Total amount of fuel consumed to perform everyday tasks per hectare
Soil management	Composite indicator of soil management that includes tillage practices and soil cover practices
Fertilisation and pest management	Composite indicator that includes fertilisation practices and pest management practices
Output	
Revenue	Total value of farm output (excluding subsidies) per hectare

The economic results are measured in our analysis using the value of output/revenue and not an alternative economic performance indicator like value added and net profit as suggested in previous studies (Kuosmanen and Kortelainen, 2005; Gómez-Limón et al., 2012). This indicator was adopted, since the economic results of olive farms during the period 2016-2018 were poor due to unfavourable weather conditions and olive fly problems. Many of the sample farms had negative net profit and some even gross margin, which poses a problem for the implementation of the DEA methodology. Therefore, for computational reasons the output value was used to estimate the level of economic activity. However, even if costs are not included in the analysis, practices regarding the main cost elements are used as environmental burdens, or in the words of the traditional DEA, as inputs. Water and fuel consumption are included in the model as well as practices that approximate the level of fertiliser and pesticide use, which constitute the main costs of olive farms (see also De Gennaro et al., 2012). The two production elements that are not included in the model are labour and capital but as argued by (Kuosmanen and Kortelainen, 2005) these inputs are not included in eco-efficiency measurements as they represent income for society (wages and rents). Therefore, though the use of output value is not the ideal indicator for economic results, the fact that all main inputs of the production process are considered as environmental burdens minimizes the shortcoming.

Table 2: Descriptive statistics of the variables used in the DEA analysis for the total farms and per agroecological type.

	Total farms	**Medium input**	**Conservation**	**Organic**	**Low input/ Integrated**	**Agroecological**
Variable	Mean (Standard deviation)					
Water consumption (lt/ha)	1119 (2958)	2003 (4381)	967 (1710)	1321 (2106)	1581 (1568)	1828 (1693)
Fuel consumption (lt/ha)	56 (115)	203 (281)	35 (91)	42 (91)	24 (43)	25 (50)
Soil management-inverse (dimensionless)	0.19 (0.21)	0.31 (0.38)	0.13 (0.01)	0.17 (0.17)	0.14 (0.10)	0.13 (0.05)
Fertilisation and pest management-inverse (dimensionless)	0.71 (1.05)	0.16 (0.12)	0.76 (1.24)	0.88 (1.31)	0.11 (0.02)	0.11 (0.02)
Revenues (€/ha)	2389 (1853)	2065 (2165)	2197 (1902)	2977 (2270)	3678 (1638)	3724 (1877)

Table 1 contains a short description of the definitions of the variables used in the DEA analysis and Table 2 summarizes the statistics for all farms but also per agroecological fam type, as discussed in the *Results* section.

The next step of our analysis involves the second-stage regression analysis that is performed to investigate the association of the eco-efficiency scores that the DEA model provides with certain characteristics of the farm and farmer. The truncated regression analysis was performed (see for example Soliman and Djanibekov 2020) using the set of explanatory variables presented in Table 3. The variables that were used in the truncated regression analysis involve demographic characteristics of the farmer (*education, sex, age, experience*), characteristics of his economic activity (*market orientation, income from olives* and *income from farming)* as well as objectives of the farmer (*producing high quality products* and *protecting the environment for future generations*).

The truncated regression analysis was chosen over the Ordinary Least Squares (OLS) regression, since the estimations performed by the OLS regression analysis are considered biased and inconsistent, due to the fact that the dependent variable consisting of the efficiency scores is censored (Samut et al., 2016). Therefore, it is better to have the estimations done by Tobit or truncated regression, however the use of truncated regression models in generally preferred and considered more appropriate (Simar and Wilson, 2007; Dai et al., 2016; Li et al., 2017).

The statistical analysis as well as the DEA analysis were performed in STATA/SE 13.0.

Table 3: Definition of variables used in the second-stage regression analysis.

Variable	Definition
Market orientation	Revenue (excluding subsidies) to Revenue plus subsidies ratio
Education of owner	Ordinal variable that takes the value 1 for primary education, 2 for middle school and high school and 3 for higher education
Sex of owner	Binary variable that takes the value 1 for male and 0 otherwise
Age of owner	Number of years
Experience of owner	Number of years of experience in farming
Income from olives	Percent of farm income that comes from olive cultivation
Income from farming	Percent of family income that comes from farming
Producing high quality products	Variable measured in Likert scale indicating farmer's objective (1=not at all important, 2=Unimportant, 3=Neither important nor unimportant, 4=Important, 5=Very important)
Protecting the environment for future generations	Variable measured in Likert scale indicating farmer's objective (1=not at all important, 2=Unimportant, 3=Neither important nor unimportant, 4=Important, 5=Very important)

4.5.4 Results

The summary statistics presented in Table 2, indicate the necessity of the use of an aggregate indicator to estimate eco-efficiency of the sample farms, as already discussed in the *Introduction section*. As we can observe from the average value and the standard deviation of the variables included in the DEA model, the selected indicators of environmental burden vary significantly across agroecological farm types[30]. Some farm types perform better when a specific environmental impact (or performance) indicator is examined but poorly when it comes to another. This, as already mentioned, is due to the fact that the use of multiple simple indicators does not take into account substitution possibilities between environmental burdens which can be confusing for policy makers to translate (Kuosmanen and Kortelainen, 2005).

Let us, for example, examine the performance of conservation farms. These farms -by definition-perform well when it comes to the S*oil management* indicator (the inverse of the indicator is included in the table, which means that low values indicate better environmental performance). This farm type also performs well when it comes to *water* and *fuel consumption* but quite poorly when it comes to the indicator of the *Fertilisation and pest management* (again the inverse of the indicator is used, meaning that lower values correspond to better environmental performance). The overall environmental performance of the farms included in this farm type cannot be estimated unless a single indicator is used, which in our study is the DEA score.

Another interesting observation of the summary statistics of Table 2, regards the performance of organic farms. As can be seen when the simple indicators are examined, this agroecological farm type performs quite well in most of them, with the exception of the *Fertilisation and pest management*

[30] The environmental indicators were also examined relative to the revenues produced.

indicator, which seems as a paradox, given the fact that organic farms use less inorganic fertilisers and pesticides. But this may well be the outcome of overuse of other practices and inputs allowed in organic production, like animal manure. Indeed, when the costs of animal manure are compared between organic and non-organic farms in the sample, it can be observed that they are almost double in organic production. Since the price of animal manure does not differ significantly between organic and conventional farms, this difference is mainly attributed to the amount of manure used in organic agriculture. Accordingly, low input/integrated and agroecological farms seem to perform well in all indicators, while medium input farms perform poorly when it comes to *fuel* and *water consumption* but better when it comes to *Soil management* and *Fertilisation and pest management*.

Let us now examine the overall environmental performance of the sample farms by performing the DEA analysis. The main findings of the eco-efficiency analysis are presented in Table 4. The average eco-efficiency is quite low, estimated at 0.39. This result indicates that there is a lot of room for improvement of the overall environmental performance of the sample olive farms. Furthermore, as indicated by the results of Table 4, low-input/Integrated farms are indeed very eco-efficient compared to the rest of the farms, characterised also by low variation of the efficiency scores. Similar results are found for agroecological farms. Medium input farms are also very eco-efficient, due to the fact that they receive a very good score in the *Fertilisation and pest management* indicator. Organic and conservation farms have a lot of room for improvement since they are characterised by smaller eco-efficiency scores with high variation.

The traditional efficiency concept, suggests that the efficiency score indicates the maximum feasible equiproportionate reduction of environmental burdens that can be achieved, given the level of output, which is in our case 61%. In the eco-efficiency analysis and given the environmental indicators used in the model, a somewhat different interpretation is more appropriate. As Kuosmanen and Kortelainen (2005) suggest, the DEA scores assigned to each eco-inefficient farm can provide guidance on efficiency improvements. Such improvements may refer to the practices that this farm should implement or on adjustments it needs to make to approximate more the efficient farms. For example, by combining the data from Tables 2 and 4, it can be deducted that if the relatively eco-efficient low-input and agroecological farms wish to improve their performance they should perhaps try to improve their *water* use, by adopting more efficient water management practices, while organic farms should also try to improve their *Fertilisation and pest management* practices.

Significant room for eco-efficiency improvement of olive groves is also identified in the study of Gómez-Limón et al. (2012) as well as in the study of Beltrán-Esteve (2013). The former study estimates that olive groves produce on average 262% more environmental pressures compared to a virtual efficient farm that maintains the same output, while the later study estimates that the environmental burdens can be reduced by 45-49% on average (depending on the farm type) while keeping the output constant. These eco-efficiency scores are lower than technical efficiency scores estimated in the majority of studies that focus on olive groves in the Mediterranean basin (Lachaal et al., 2005; Lambarraa et al., 2007; Kashiwagi at al., 2012; Jurado et al., 2017; Niavis et al, 2018; Stilitano et al., 2019; Raimondo et al., 2021). On the other hand relatively low technical efficiency scores (0.54 on average) are estimated by Tzouvelekas et al. (2001) for Greek conventional olive groves indicating that there is a lot of room for improvement regarding the utilisation of inputs. It should also be noted that the technical efficiency scores that were estimated for the olive farms of our sample are also higher compared to the eco-efficiency scores estimated in this study (see also LIFT Deliverable 3.1).

Table 4: Descriptive statistics of Environmental Efficiency (EE) for the sample farms and per agroecological type.

Agroecological type	Mean	Standard Deviation	CV	Min	Max
Total farms	0.39	0.30	77%	0.02	1
Organic	0.42	0.34	81%	0.04	1
Conservation	0.36	0.30	83%	0.02	1
Low input/Integrated	0.66	0.24	36%	0.35	1
Medium input	0.68	0.38	56%	0.04	0.98
Agroecological	0.65	0.27	42%	0.35	1

Eco-efficiency scores were further examined using truncated regression analysis, as mentioned in the sections *Data* and *Method*s. The results are presented in Table 5. One important finding of the regression analysis is that *market orientation* has a positive and statistically significant effect on the EE score (based on the coefficient and the p-value of this variable). This finding indicates that subsidies have a negative effect on the eco-efficiency of farms and is in accordance with the findings of technical efficiency analysis performed for Deliverable 3.1. Other studies that investigate the role of subsidies on farm environmental performance have come to the same conclusion (Van Passel et al., 2007), as well as studies that focus on the technical efficiency of olive farms in Greece and the Mediterranean region (Zhu et al., 2011; Lambarraa and Kallas, 2010).

The *education* of the farmer also seems to positively affect eco-efficiency of the farm, as opposed to his experience. The positive effect of education is a common finding of many studies that focus on the explanation of eco-efficiency (see for example Van Passel et al., 2009; Picazo-Tadeo, et al., 2011; Godoy-Durán et al., 2017). However, the exact opposite results were found in the estimation of technical efficiency of the farms, that seems to be explained by experience rather than education.

What is also important to emphasize is that the higher the *percent of income that comes from farming* the higher the eco-efficiency. In other words, farmers that are more involved in the activity tend to receive higher eco-efficiency scores. Similar findings have been observed by Gómez-Limón and Sanchez-Fernandez (2010) regarding agricultural sustainability, which increases when the income from farming increases. On the other hand, the percent of farm income that comes from olive cultivation has a negative effect on eco-efficiency, though not statistically significant. This means that the presence of other cultivations may enhance eco-efficiency as opposed to olive monoculture.

Finally, it seems that farmers that place more value on *producing high quality products* appear to have higher eco-efficiency scores, as opposed to those that state they place more emphasis on *protecting the environment for future generations*. These last findings may suggest that the actual reason for implementing environmentally friendly farming practices may be farmers' focus on quality products and not on environmental concerns per se. This may not be such an unexpected finding, if we keep in mind the increasing demand for high quality products and consumer awareness on health and environmental issues. Furthermore, as Keating et al (2010) emphasize, as far as agriculture is concerned, the concept of eco-efficiency maybe interpreted as the production of more high-quality products while simultaneously reducing the use of inputs soil, water, energy, work and capital.

Table 5: Results of the Truncated Regression analysis.

Variables	Coefficient	Std. Err.	z	P>z	[95% Conf. Interval]	
Market orientation	1.858538	0.9736596	1.91	0.056	-0.0497992	3.766876
Education of owner	0.4388131	0.2416445	1.82	0.069	-0.0348014	0.9124276
Sex of owner	0.2603761	0.2499269	1.04	0.298	-0.2294717	0.7502239
Age of owner (in years)	-0.008905	0.0106067	-0.84	0.401	-0.0296937	0.0118838
Experience of owner (in years)	0.0064778	0.0090149	0.72	0.472	-0.0111912	0.0241467
Income from olives (%)	-0.0174835	0.0114132	-1.53	0.126	-0.039853	0.004886
Income from farming (%)	0.0113014	0.0056847	1.99	0.047	0.0001597	0.0224431
Producing high quality products	0.3614931	0.2069177	1.75	0.081	-0.044058	0.7670443
Protecting the environment for future generations	-0.2932392	0.1722911	-1.7	0.089	-0.6309235	0.044445
Constant	-1.184381	1.300053	-0.91	0.362	-3.732437	1.363676

4.5.5 Discussion and conclusion

Eco-efficiency is often used to measure environmental performance of production units including farms. Though establishing eco-efficiency does not necessarily guarantee sustainability, it may be considered as a step in the right direction, since eco-efficiency indicates ways to maintain the same level of output while minimising environmental burdens.

This study focuses on the estimation of the eco-efficiency of Cretan olive farms taking into account their main farming practices in terms of water and fuel use, fertilisation and pest management as well as soil management. To estimate eco-efficiency, we employ the DEA analysis, traditionally used to estimate technical efficiency of production units. This methodology allows us to use the DEA scores as a single aggregate indicator of eco-efficiency instead of multiple simple indicators. The degree of uptake of ecological practices is also considered in the analysis, since the results are presented for the total farms in the sample as well as for organic, conservation, low-input/integrated, medium input and agroecological farms.

The results of the analysis indicate that, though some farm types perform well in some environmental indicators, they may perform poorly in some others, therefore making it difficult to decide on their overall environmental performance. This demonstrates the usefulness of the methodology implemented in this study as a way to aggregate environmental burdens, consider substitution possibilities among them and facilitate the work of policy makers. One example from our study, is the case of the medium input farms, that although they perform poorly on most simple indicators their overall eco-efficiency score is quite satisfying. What is also worth mentioning about the medium input farms is the fact that their technical efficiency was not found to be as high as their eco-efficiency. In other words, medium input farms have a higher environmental and not economic performance.

On the other hand, organic farms seem to have a higher economic rather than environmental performance, in terms of technical and eco-efficiency. Organic farms may be restricted to follow some practices or guidelines regarding the use of specific inputs (like inorganic fertilisers) but may be overusing other inputs (like water or animal manure). This indicates that further investigation is required on the objectives and motives of organic producers. After all, the second stage regression analysis indicated that subsidies (which are significant in the case of organic farms) have a negative impact on eco-efficiency. All the above findings need to be carefully considered in agricultural planning and policy making.

It should be however emphasised that further research is required regarding the eco-efficiency scores and their determinants. The role of farmers objectives and attitudes need further investigation, especially since it seems that the eco-efficiency scores are positively affected by objectives regarding the production of quality products and negatively affected by purely environmental objectives. This may well be an indication of the influence of consumer demands for quality (and eco-friendly) products on the cultivation practices followed in the farm.

One limitation of the analysis is the use of revenues as opposed to value added to estimate the production level. This path was chosen due to the weather conditions and the olive fly problems that farmers faced during the reference period that affected revenues and yielded negative profits in some cases, making it difficult to use other economic indicators in the DEA analysis. Future research maybe required to estimate how the use of other indicators like value added would affect the results of the eco-efficiency analysis, since cost elements would be more profoundly included in the analysis. For example, we would expect the eco-efficiency scores of medium input farms to be closer to their technical efficiency scores. Regardless of its limitations however, the analysis has demonstrated that eco-efficiency is a useful concept, and its investigation can shed light into aspects of farming that are else neglected.

4.5.6 References

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5 Bioeconomic modelling

5.1 Development of a bioeconomic model of pasture-based livestock farms (Teagasc)

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5.1.1 Introduction and description of case study region

The growing population and emerging market trends for meat products are creating challenges and opportunities for the agricultural industry and in particular those temperate regions where ruminant based meat and dairy is the major product output. With European and national policy focus evolving to foster the competitiveness and sustainability of farming systems in Europe (e.g. Agro-ecological approaches to farming, EIP-AGRI, EU Green Deal) there is an increasing demand for micro level analysis of the environmental, financial and social performance of agricultural systems. This paper provides a case study of Irish sheep flocks aimed at investigating the sustainability of these ruminant meat production systems from an environmental and economic perspective (Garnett et al., 2013).

International marketing initiatives and eco labels are increasingly being used to promote the sustainability of production systems and certify the environmental impacts of value chains based on initiatives to improve the environmental performance of products (Chen et al., 2017; Bord Bia, 2016). At the same time, national strategies to increase the value of agricultural exports by growing agricultural production pose environmental challenges (Buckley et al., 2019).

This study explores these issues by comparing the farm level economic and environmental performance of Irish sheep farms based on a bioeconomic model of the sheep production system using the nationally representative Teagasc National Farm Survey (NFS) panel data (Hennessy et al., 2016) and biological information linked to livestock. NFS data enable the evaluation of the farm level Carbon Footprints (CF) and land occupation for the range of Irish sheep flocks. The environmental performance of distinct sheep farming systems operating at different levels of production intensity and input use is presented and compared with key financial and technical performance outcomes.

The purpose of this study is to develop a nationally representative modelling framework to estimate and compare the farm level profitability, carbon footprint and land occupation of ruminant grazing farms in Ireland. Farm level scenarios will capture the information on the economics (e.g. input, output prices etc), environmental footprint (farm Global Warming Potential) the institutional context (contribution of direct payment supports etc) and farm environment conditions (e.g. spatial context, agronomic constraints).

5.1.2 Data and methods

In order to estimate emissions and financial performance at a farm level this study employs NFS data which collects detailed production information on animal activities and associated costs, the area, yields and input costs of home-grown crops, and pasture inputs and costs.

The study modelled the full sample of 3235 sheep farm enterprises (farm year records) over the 6 year period 2010 to 2015. 506 were classified as hill farms and 2729 lowland farms. The average farm size was 50 hectares for hill farms and 42 hectares for lowland farms. On average, lowland farms demonstrate higher levels of technical performance across the range of parameters analysed. Hill farms are typically managed on upland rough grazing, have lower lambing and stocking rates than lowland breeds managed on higher quality pasture. Hill farms are, on average, larger than lowland farms with larger flocks but are relatively more extensive. Average stocking rates recorded were 7.1 and 8.9 ewes/ha for hill and lowland farms respectively. Weaning rates were .9 lambs/ewe and 1.2 lambs/ewe respectively.

In terms of inputs, hill farms are shown to exhibit slightly higher direct costs per unit output compared to lowland farms. In line with their more extensive nature, these farms get a higher proportion of DM intake in the form of grazed grass compared to lowland farms. Lowland farms on average spread more nitrogen fertiliser (92.4kg/ha vs 67.2 kg/ha) and use more fuel (34.6L/ha vs 26.7L/ha) per unit area than hill farms.

This study performs a Life Cycle Assessment (LCA) of the environment outputs from Irish sheep farms. While the analysis presented in this study follows the ISO standard layout, the Carbon Footprint calculations represent a partial LCA.

The CFs for sheep farms were calculated in this study according to a cradle to farm gate system boundary. This is a holistic systems approach that aims to quantify the potential environmental impacts e.g. GHG emissions, generated throughout a product or processes life cycle within a defined boundary. Thus the analysis accounts for all GHG emissions from the farm up to the point of product sale from the farm (cradle to farm gate).

The resources used and emissions related to sheep enterprises were quantified in the inventory analysis stage through a sheep farm systems model and crops sub model briefly described here. This crops sub model was developed to estimate emissions from crops used for livestock feed. Emissions factors were calculated based on input information gathered from national research and Teagasc production specialists (CSO, 2017a; DAFM, 2012; Phelan, 2017; Teagasc, 2011), IPCC (2006) guidelines and the international LCA literature (O'Brien et al., 2015; Nemeck et al., 2007).

The farm (cradle to farm-gate) LCA analysis includes the emissions from livestock (enteric fermentation), inputs used on-farm (pesticides, fuel, phosphorus (P) and potassium (K) and ammonia nitrate fertilisers) along with the inputs used in the production of purchased feeds produced off-farm (pesticides, fuel, P,K and ammonia nitrate fertiliser) and the emissions released in the manufacturing process of these same inputs (off-farm production processes).

The land use change emissions for a representative sheep ration (0.23kg CO_2 per kg concentrate dry matter fed) are estimated by computing the land use change emissions associated with the production of relevant constituent feed ingredients based on the associated crop information for source countries (Vellinga et al., 2013) and emissions factors from the Carbon Trust (2013), and are in line with the approach of O'Brien et al. (2015). Land area was quantified in hectares, including land required to produce home-grown forage and crops and land for imported feedstuffs.

The climate change impact of GHG emissions from sheep production was calculated in terms of CO_2 equivalents using 100 year global warming potential (GWP) The Global Warming Potential (GWP) factors are a relative measure of how much heat a greenhouse gas traps in the atmosphere and was developed to allow comparisons of the global warming impacts of different gases. In this study IPCC (2006) GWP values are applied to determine the overall contribution of CO_2, CH_4 and N_2O to total emissions. Accordingly, all GHG emissions calculated are estimated in terms of the reference gas CO_2

equivalents where the GWP of 1 kg CO_2 is 1, 1 kg CH_4 is 25, and 1 kg N_2O is 298, assuming a 100-year time horizon.

The other resource use measure examined in this study is the equivalised land area occupied by sheep production systems. Land occupation was quantified in m^2/kg of LW and included land required to produce homegrown forage (grass and grass silage or hay) fodder crops used for the sheep enterprise, and the equivalised land footprint of purchased bulkfeeds and imported feedstuffs (presented in hectare equivalents).

Analysis of economic performance is undertaken at the enterprise level and broken down by hill and lowland enterprises, taking into account their differential production systems. To benchmark the different sheep farming systems, a gross margin analysis is performed. Financial results are presented for the average of lowland, hill and all farms. Lowland farms are further ranked on the basis of gross margin per hectare, and grouped into three categories; the top third, middle third and bottom third of performing farms.

5.1.3 Results

Figure 1 describes the distribution of gross output across sheep enterprises over the sample period. The average value of gross output per hectare for the sample of sheep flock subsystems is measured relative to their forage area (hectares) and number of sheep livestock unit. The difference between the two measures is largely due to the difference in the average stocking rate across systems. Early season enterprises have the highest gross output in both unit measures (€1047/ha €530/lu). The higher per livestock output from the early season system is facilitated through indoor housing and a greater emphasis on more expensive, concentrate based diets required to meet the nutritional requirements of ewes lambing earlier in the season, when grass is in short supply (Flanagan et al., 2001). The predominant mid-season system has the second highest output per LU and per hectare (€849/ha, €442/lu) with farms typically lambing down in the spring with the onset of grass growth (Keady et al., 2009). The hill sheep systems have the lowest output per hectare output as would be expected, given their extensive nature and upland grazing. Blackface Mountain systems exhibit the lowest stocking rates (0.6ewes/ha) and output per unit (€153/ha, €262/lu) of all the systems analysed.

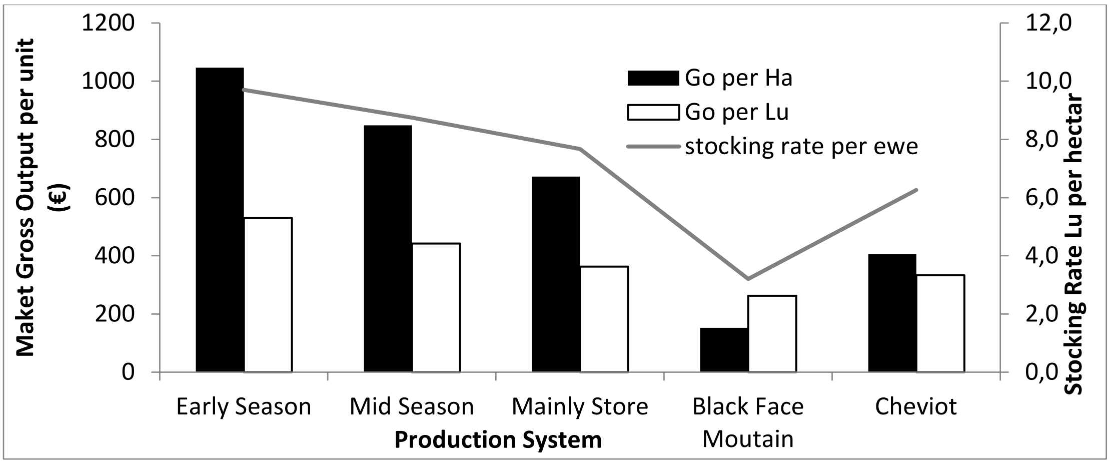

Figure 1: Distribution of Gross Output and Stocking Rates by sheep Sub-System

Lowland farms exhibit higher gross margins driven by significantly higher gross output per unit hectare. Hill farms are much more dependent on direct income support: of the €206/ha gross margin earned on hill farms over the period €110/ha or 54% of this is attributable to subsidy payments, whilst on lowland farms almost 80% is earned from the market. Analysing midseason lowland farms, the top performing group earned an average gross margin of €937 per hectare; farms in the bottom group earned an average gross margin of only €198 per hectare. This means that the top producers earned, on average, almost 5 times more per hectare than their counterparts in the bottom group whilst a breakdown of the trend in gross margin (2000 – 2015) highlights that the gap between the top and bottom third of mid-season lowland lamb producers has been growing. The best performing farms can be seen to achieve significantly higher levels of output while simultaneously keeping a control over direct cost. Higher output levels are achieved through better technical performance and reflected in higher stocking rates and weaning rates.

In terms of direct costs per hectare, feed costs represent the major cost item. Over the sample period, feed costs contributed on average over 73% of total direct costs across all sheep farming enterprises. If feed costs are broken down into its components, concentrate costs are the single largest expense item, contributing on average over 44% of direct costs across all enterprises for the same period. The share of expenditure attributable to concentrates is lowest in the top performing farms (41%) and highest in the bottom third of farms (45%) while the opposite is true for pasture costs (33% vs 29%).

In line with expectations, grass represents the most important and cheapest feed on a cost per unit energy basis, contributing over 76% of energy supply to livestock and at a cost of little over one cent per unit energy across all farms. Concentrates is the second most important feed source, supplying 12.3% of energy to livestock at a cost of 24 cent per UFL. This makes concentrate feed the most expensive feed source.

GHG emissions from sheep farms (Table 1) are expressed in terms of the Carbon Dioxide (CO_2) equivalent per kg of live weight equivalent of sheep produced, unlike previous LCAs of sheep farms which allocated emissions between products based on economic allocation (O'Brien et al., 2015).

The average CF of lowland farms was estimated at 9.8kg of CO_2-eq/kg LW, which was 13% lower than the average CF estimated for hill farms. The average CF of lowland farms was within the range previously estimated by O'Brien et al. (2015) whilst the CF of hill farms diverged significantly. All sheep farms analysed in this study operate grass based grazing systems. Estimates of the breakdown of energy supply from the range of feed stuffs support this and show that on average across all farms grass contributed 76.4% of flock energy demands. As would be expected, given their more extensive nature, grass supplied a greater proportion of energy to livestock on hill farms (81%) when compared to lowland farms (75.5%).

Taking into account the carbon sequestration value of grassland reduces the carbon footprints on hill farms to 9.99kg of CO_2-eq/kg LW (12% reduction) and lowland farms to 8.6kg of CO_2-eq/kg LW (10% reduction). In line with O'Brien et al. (2015), the carbon sequestration rate had a relatively larger impact on reducing emissions for more extensive farms. This is evident when comparing the average of hill to the average of lowland farms or average top and bottom performing midseason farms to the bottom performing one.

Looking at the breakdown of emissions across all sheep farms (Table 2), animal activities represent the largest source, with Tier I estimates of enteric fermentation and manure management comprising (64%) and (6%) of total emissions respectively. Other emissions include those emissions from soils (14%) and total emissions associated with feed production (16%). A detailed breakdown of emission from feed production included emissions associated with inputs used in the feed production process (field processes, transport, manufacturing and processing of feed grains, mixed rations and forage) and land use change are presented in (Table 2). The GHG emissions associated with the cultivation, processing, and transport of concentrate feed (but excluding non-recurrent land use change emissions) were the largest, contributor of emissions associate with feed input provision 49% (7.8% of total emissions). The off-farm emissions from land use change (LUC) associated with the production of Brazilian soybean meal (protein ingredient in representative concentrate feed) accounted for the next largest proportion of emissions from feed inputs at 20% (3.2% of total farm emissions), followed by on-farm emissions from artificial N fertiliser application at 11% (2.5% of total).

Table 1: Carbon footprint (CF) of sheep meat production (kg of CO_2/kg LW)

				Midseason Farms ranked by GM/ha		
	All farms	Hill	Lowland	Bottom	Middle	Top
Carbon Footprint	9.88	11.33	9.84	10.47	8.44	7.47
Carbon Footprint excluding Land use change[1]	9.52	11.04	9.12	10.03	8.13	7.18
Carbon Footprint with Carbon Sequestration	8.89	9.99	8.58	9.13	7.54	6.49

[1]Nonrecurrent land use change emissions from the conversion of grassland to arable land and from the cultivation of South American soybean and southeast Asian palm concentrate feedstuffs

Table 2: GHG emissions profiles of Irish sheep flock Diets

					Bottom, middle, and top third of Midseason lowland farms ranked by gross margin/ha		
GHG emissions and source as CO_2 equivalent	**Emissions Location**	**All Sheep Farms**	**Lowland**	**Hill**	**Bottom Third**	**Middle Third**	**Top Third**
Methane (CH_4) Livestock Activities							
Enteric Fermentation	On-Farm	64.4%	62.4%	70.7%	58.7%	62.2%	64.1%
Manure Management and excretion		6.2%	6.1%	6.3%	5.7%	6.2%	6.3%
Nitrous oxide (N_2O-N) Livestock Activities							
Manure storage and spreadings, & excretion on pasture		13.6%	14.8%	10%	14.4%	14.7%	15.2%
Nitrous oxide (N_2O-N)							
Synthetic N fertiliser application	On-farm	2.5%	2.8%	1.5%	4.1%	2.9%	2.2%
N leaching		0.2%	0.2%	0.1%	0.3%	0.2%	0.2%
Atmospheric deposition(6)		0.1%	0.1%	0.0%	0.1%	0.1%	0.1%
Carbon Dioxide (CO_2)							
Fuel Use (Diesel)	On-farm	0.7%	0.7%	0.7%	1.1%	0.6%	0.5%
Fertiliser Application (Urea applied)	On-farm	0.1%	0.1%	0.0%	0.2%	0.1%	0.1%
Lime application	On-farm	0.4%	0.4%	0.3%	0.6%	0.4%	0.2%
LUC from on-farm arable land (home-grown feeds)[1]	On-farm	0.5%	0.6%	0.1%	0.5%	0.5%	0.8%

Fertiliser Production (Urea, P, K, and Ammonia Nitrate fertiliser applied)	Off-farm	0.6%	0.6%	0.3%	0.9%	0.7%	0.5%
Concentrate production[2]	Off-farm	7.8%	8.1%	6.7%	8.5%	7.8%	7.0%
Carbon dioxide, CO_2 from land use change LUC[3]	Off-farm	3.2%	3.3%	2.7%	3.5%	3.2%	2.8%
Other Inputs[4]	Off-farm	0.5%	0.4%	0.8%	0.5%	0.3%	0.4%

[1]Nonrecurrent land use change emissions from the conversion of grassland to arable land.

[2]The GHG emissions associated with the cultivation, processing, and transport of concentrate feed, but excluding nonrecurrent land use change emissions.

[3]Nonrecurrent land use change emissions from the cultivation of South American soybean feedstuffs used as a constituent in concentrate ration.

[4]Emissions from the production of purchased forage, milk replacer, fuel, pesticides and plastic.

5.1.4 Discussion and conclusion

In the context of sheep farming, there are a number of differential production systems which provide a significant range of both market and non-market outputs, all of which must be taken into account when comparing the relative sustainability of systems (Ripoll-Bosch et al., 2013).

Results of financial performance and feed analysis highlight that sheep farms operate grass-based production systems and that the best performing lowland flocks are focused on the production and use of grazed grass as the cheapest feed source. Supplementary concentrate feed on the other hand is shown to be the most expensive feed per unit energy with poorer financial performing farms more reliant on it as a key source of nutrition. The more profitable lowland enterprises are characterised by higher technical performance, stocking and weaning rates, greater production intensity and greater emissions efficiency on a per unit basis and is in line with previous studies in comparable production settings (Hyland, 2016; Jones et al., 2014a; O'Brien et al., 2015). Improved technical performance is reflected in the average carcass output per hectare of 332 kilos on the top third of lowland mid-season farms, versus 167 kilos on the bottom third of farms. This higher level of lamb output per hectare, combined with tighter control of direct costs is reflected in higher enterprise profitability.

In line with previous studies (Jones et al., 2014b), extensive hill production systems demonstrated lower overall emissions, lower production efficiency and higher GHG emissions per unit output. However, there are a range of other environmental sustainability measures that are not analysed in this study. O'Brien et al. (2015) also analysed nutrient surpluses, acidification and eutrophication as part of an LCA and found more intensive sheep farms had the greatest negative environmental impact for these factors. This highlights the potential conflict between carbon efficiencies and other environmental objectives not analysed here (Jones et al., 2009; Maier et al., 2001).

The farm level modelling framework developed in this study can be readily extended to estimate CFs for cattle and dairy production systems as recorded in the NFS. There is also the potential to develop the analysis in this study to produce a full LCA of sheep farms. This would require a Tier II estimate of Enteric Fermentation emissions in line with LCA protocols. Given the structure of NFS data, additional assumptions around animal performance, growth rates, and dry matter intake (DMI) would need to be made in conjunction with livestock specialists and in order to describe the farm level variability in livestock performance and related emissions more accurately.

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5.2 Plot sizes and farm-plot distances as driver of economic farm performance along the degree of ecological approaches (UBO)

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with some sections being identical to the original paper.

5.2.1 Introduction

Plot sizes and farm-plot distances affect the economic performance of agricultural production. Increasing plot sizes provide economies of scale by reducing unproductive turning and driving times of field operations. A resulting reduction in input and labour requirements decrease average costs of production (Herrmann and Papesch 1996; Jahns et al. 1983; Latruffe and Piet 2014; Looga et al. 2018; Lu et al. 2018). Increasing farm-plot distances have the opposite effect by increasing resource requirements and costs of field operations due to higher transport costs (Jahns et al. 1983; Kuhlmann 2015; Latruffe and Piet 2014). The impacts of plot sizes and farm-plot distances highly depend on the type and the number of field operations (Jahns et al. 1983). The type and the number of field operations as well as the amount of intermediate and final products transported depend highly on the crop rotation and the crop management (Kuhlmann 2015) and thus differ between conventional and organic farming systems. These differences are, for example, caused by restrictions on the use of synthetic fertiliser and a ban on chemical synthetic pesticides in organic production systems. As a result of the differences, economic effects of plot sizes and farm-plot distances likely differ between these farming systems and might drive economic performance gaps between conventional and organic farming systems.

This study addresses a gap in the literature by analysing the effects of plot sizes and farm-plot distances on the economic performance in organic and conventional farming systems. In this context, a large-scale sensitivity analysis on the effects of plot sizes and farm-plot distances on multiple economic indicators is conducted. Thereby, we aim to assess if scale effects work differently in organic and conventional farming systems, especially considering that organic production programs are typically more diversified with regard to crop production but are often operated as mixed farms (Britz 2019). As the conversion to organic farming can be associated with considerable changes in the farms production program, the whole farm management must be considered rather than changes of individual field operations for a single crop. Therefore, this study is conducted at the level of the whole farm for three case studies, considering detailed definitions of activities for the different farming systems such as field operations with related machinery costs and intermediate resource requirements, yields and monetary returns, including subsidies granted to organic production (Britz 2019).

5.2.2 Description of case study region

As part of the National Sustainable Development Strategy, the German government aims to increase the share of organic farming on productive agricultural land from 9% in 2018 (BMEL 2018) to 20% by 2030 (German Federal Government 2018). In 2018, 32,000 organic farms managed more than 1.5 million hectares, of which 56% are permanent grassland and 42% arable land (BMEL 2018). Most of the arable land under organic production is dedicated to the cultivation of cereal grains, plants harvested green (including fodder legumes) and grain legumes (e.g. lupines, beans and peas) (Destatis 2017). 70% of the organic farms are engaged in livestock production, 75% of which produce cattle and 10% pigs.

Table 1: Key attributes of the case study farms

		Arable Farm		Pig Fattening Farm		Dairy Farm	
		Conventional	Organic	Conventional	Organic	Conventional	Organic
Farm size	ha	100	100	56	42	100	100
Number of livestock places			2500 laying hens	800	240	100	105
Crop shares	%	Sugar beet (35%) Wheat (25%) Barley (25%) Potatoes (15%)	Grass-clover (17%) Grain peas (17%) Triticale (17%) Potatoes (13%) Barley (12%) Wheat (8%) Spelt (8%) Pumpkin (4%) Grain maize (4%) Catch crop (30%)	Wheat (46%) Barley (27%) Silage maize (27%) Catch crop (27%)	Grain maize (25%) Field bean (20%) Triticale (20%) Barley (20%) Wheat (10%) Oat (5%) Catch Crop (15%)	Grass-clover (32%) Permanent Grassland (15%) Grain maize (15%) Silage maize (12%) Rye (11%) Barley (7%) Wheat (5%) Oat (2%) Catch crop (10%)	Grass-clover (75%) Permanent grassland (15%) Whole crop silage (10%) Catch crop (10%)
Average farm-plot distance	km	0.5		1.1		2	
Average plot size	ha	5.1		6		4	

Notes: Key attributes of the case study farms as reported in face-to-face interviews.

In the western German states of North Rhine-Westphalia and Lower Saxony, the share of organic farming in agricultural land is the lowest in Germany, at 6% and 4.7% respectively (BMEL 2020; German Federal Government 2018). We therefore analyse as case studies three farms located in Western Germany. An arable farm, a pig fattening farm and a dairy farm are selected to cover the relevant farm types in this region. We collect with semi-structured face-to-face interviews relevant technical and economic information on crop and livestock production, covering for example the production program as well as prices and yields where available. Key results are reported in Table 1. All three farms have been recently converted from conventional to organic production such that we receive detailed information about the farm program under both systems.

5.2.3 Methods and Data

The effects of plot sizes and farm-plot distances in conventional and organic farming systems are evaluated by linking big data on field operations to detailed case study data for a large-scale sensitivity analysis (see Figure A.1). The large-scale database from the *Kuratorium für Technik und Bauwesen in der Landwirtschaft (KTBL)* reports big data on necessary field operations with details on costs of machine applications and related machinery costs and intermediate input requirements, including, for instance, machinery depreciation and costs for maintenance, lubricants and fuel as well as details on labour requirements. The data is provided in detail for 145 crops under the conventional and organic farming system, considering distinct plot sizes and farm-plot distances as well as different mechanisation levels, amounting to more than 29.5 million data records (KTBL 2019b). Based on a regression analysis, we derive from there continuous functional relations of how costs and labour requirements of field operations depend on plot sizes and farm-plot distances. We consider plot sizes of up to 40 ha, farm-plot distances up to 30 km and three mechanisation levels (with tractors of 67 kW, 102 kW and 200 kW as main machine).

We estimate for each field operation FO, crop C, mechanisation level M and farming system S the different per hectare resource requirements $\hat{Y}$ based on a polynomial regression function with plot size P and farm-plot distance D as explanatory variables:

$$\hat{Y}_{FO_{CSM}} = \beta_0 + \beta_1 P + \beta_2 P^2 + \beta_3 \sqrt{P} + \beta_4 D + \beta_5 D^2 + \beta_6 PD$$

$$\hat{Y}_{C_{SM}} = \sum_{FO} \hat{Y}_{FO_{CSM}}$$

In total, we provide 1.8 million regression functions covering 8 positions (such as fuel and labour requirements and maintenance costs) of field operations for 145 crops.

For each crop, the regression coefficients for labour and resource requirements are summed over the required field operations. This yields per hectare labour as well as intermediate resource requirements related to machine applications for a crop, as a function of plot sizes and farm-plot distances, differentiated by three mechanisation levels.

The detailed information of the case study farms are complemented by detailed planning data on costs and revenues of livestock and crop production. The economic data on livestock production provides details on revenues and costs as well as labour requirements, separated by the type of livestock and farming system (i.e. conventional or organic production) (KTBL 2019c). The information for each crop include data on yields and prices as well as expenses for agricultural contractors and direct costs (e.g. planting materials, fertilisers and pesticides) (KTBL 2019a).

By linking the regression functions to the case study data as well as the economic data on livestock production as well as revenues and direct costs of crop production, the economic farm performance of each farm is calculated as function of plot sizes and farm-plot distances Figure A.1. The functions are used to conduct a large-scale sensitivity analysis on the effects of plot sizes and farm-plot distances in the conventional and organic production system. Using this function, we generate a three-dimensional surface area for each of the economic indicators. A linear regression on the three-dimensional surfaces is performed with plot size and farm-plot distance as explanatory variables to determine the average effects of plot sizes and farm-plot distances. The function is subsequently used to calculate the economic performance of the case study farms at observed plot size and farm-plot distance and to assess average effects of plot sizes and farm-plot distances.

At the time the study was conducted, common indicators of farm performance had not yet been agreed upon. In this study, the economic farm performance is assessed considering multiple economic indicators. First, the farm profit is determined, with and without the consideration of subsidies granted for organic production. Costs of crop production are calculated including details on intermediate inputs requirements (e.g. fertilisers and pesticides) as well as costs of machine applications and related resource requirements, including labour costs. Finally, labour requirements arising in arable production and total labour requirements are determined.

5.2.4 Results

5.2.4.1 Economic performance

5.2.4.1.1 Profits

For all three farms, conversion to organic farming is in the observed period a profit increasing choice. Figure 1 shows the calculated economic performance of the three case study farms at observed plot sizes and farm-plot distances. A key reason for the higher profits under organic production is the large price premium for organic outputs. Before conversion, the average profits per hectare differ considerably between the three case study farms, with the arable farm generating a positive profit, while the pig fattening and the dairy farm face negative. We find that the profit of the pig fattening farm is higher under the organic system even without considering subsidies. In contrast, the profit of the arable farm before subsidies decreases after conversion. The change in profits before subsidies for the dairy farm is limited. Once subsidies granted for organic production are considered, all three farms achieve higher profits compared to conventional production. In the dairy farm, however, profits remain negative under the assumed wage costs of 20 € h^{-1}.

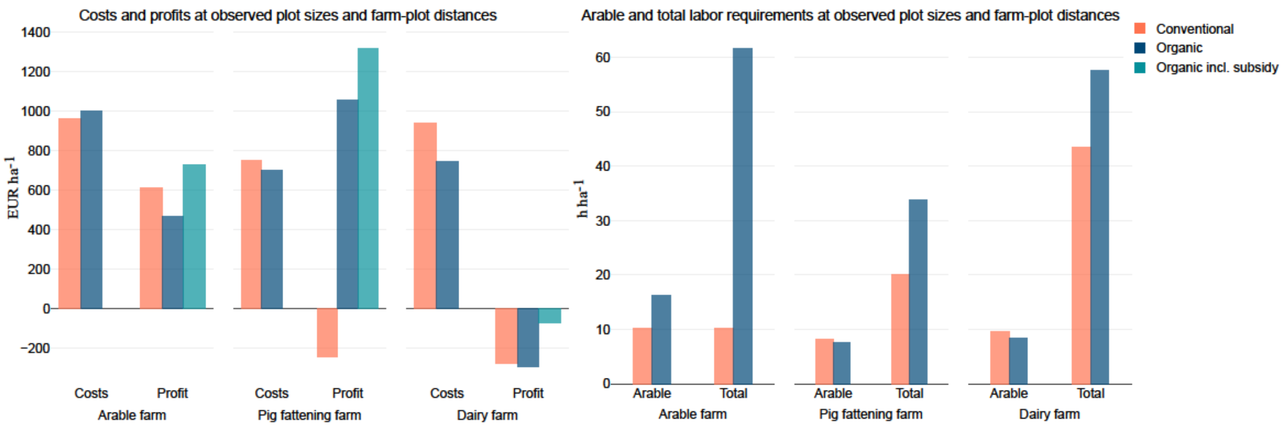

Figure 1: Overview on the calculated economic performance at observed plot size and farm-plot distance

Notes: The economic performance is presented for the conventional and organic production program at plot sizes and farm-plot distances reported by the farmers. Costs include the costs of on-farm labour, valued at 20 € h^{-1}.

5.2.4.1.2 Costs of crop production

We find that costs per hectare related to crop production are 8% lower in the organic system on average over the three case studies. The reduction reflects three drivers. First, the crop rotation shifts towards crops requiring less inputs, for example through the introduced or expanded legume production. Second, direct costs are reduced, mainly because costs for synthetic fertiliser and pesticides are omitted. Third, less frequent fertilisation and plant protection measures in organic farming cause a lower number of machine passes over the fields for most crops. This decreases expenses related to machine applications as well as related labour requirements and costs. However, the crop production costs of the arable farm slightly increase, reflecting a strong increase in labour requirements.

5.2.4.1.3 Labour requirements

Our results show lower labour requirements related to crop production after conversion in the pig fattening and dairy farm. For the arable farm, labour requirements in crop production however increase, resulting in an increase of crop production costs after conversion. This reflects rather labour intensive weed control, harvesting and post-harvest processes for pumpkin as a new crop in the rotation. The introduction of laying hens in the former specialised arable system without livestock adds considerably further labour requirements, such that in total 61.7 h ha^{-1} are required. Similarly, when including animal production, the total labour requirements of the pig fattening and the dairy farm increase after conversion. In those two farms, when switching from conventional to organic production, labour savings in crop production are offset by increased labour requirements in livestock production.

5.2.4.2 Effects of plot sizes and farm-plot distances

Table 2 presents the results of the linear regression on the three-dimensional surfaces for the three case study farms separated by farming system. The regression coefficients, i.e. the effects of plot sizes and farm-plot distances, measure the change in profits, costs and labour requirements for changes of one hectare in plot size and one kilometre in farm-plot distance, respectively. Given the relatively small effects, the intercepts show again that profits of organic production including subsidies granted to organic production are higher for all three case study farms.

As indicated by the regression coefficients in Table 2, the average effects of plot sizes and farm-plot distances are in absolute terms stronger for conventional production in all three case study farms. This is especially relevant for the pig fattening farm: an increase in farm-plot distance by one kilometre provokes an increase in costs by 11.75 € ha^{-1} under conventional compared to 6.17 € ha^{-1} under organic production. Similarly, an increase in plot size by one hectare reduces costs by -3.42 € ha^{-1} under conventional compared to -1.68 € ha^{-1} under organic production. On average over the three case study farms, the effects of plot sizes and farm-plot distances on costs and profits are 80% higher under conventional production. One reason is the higher number of machinery passes for most crops in conventional farming. This implies that overall costs increase stronger with increasing farm-plot distances and decreasing plot sizes compared to organic production.

The effects on the labour requirements follow these trends. Labour savings in crop production from larger plot sizes and smaller transport distances are on average 74% higher in conventional farming. The total labour requirements of the analysed farms, except for the conventional production program of the arable farm, mostly relate to livestock production. This strongly reduces the relevance of the analysed effects at farm level.

Table 2: Average effects of plot size and farm-plot distance on profits [€ ha-1], costs [€ ha-1] and labour requirements [h ha-1]

	Arable farm		Pig fattening farm		Dairy farm	
	Conv	**Org**	**Conv**	**Org**	**Conv**	**Org**
	EST (SE)	**EST (SE)**	**EST (SE)**	**EST (SE)**	**EST (SE)**	**EST (SE)**
Intercept						
Profit incl. org. subsidy [€ ha^{-1}]		722 (0.18)		1,313 (0.21)		-48 (0.10)
Profit without org. subsidy [€ ha^{-1}]	604 (0.18)	462 (0.18)	-253 (0.34)	1,053 (0.21)	-261 (0.26)	-272 (0.10)
Costs of crop production [€ ha^{-1}]	967 (0.18)	1,005 (0.18)	759 (0.34)	704 (0.21)	922 (0.26)	719 (0.10)
Coefficients						
Farm-plot distance (1) [€ ha^{-1}]	-7.24 (0.01)	-6.22 (0.01)	-11.75 (0.01)	-6.17 (0.01)	-13.98 (0.01)	-13.26 (0.00)
Plot size (1) [€ ha^{-1}]	1.91 (0.01)	1.44 (0.01)	3.42 (0.01)	1.68 (0.01)	2.19 (0.01)	0.66 (0.00)
Intercept						
Total labour requirements [h ha^{-1}]	10 (0.00)	62(2) (0.00)	20 (0.01)	34(3) (0.01)	43 (0.00)	57(3) (0.01)
Arable labour requirements [h ha^{-1}]	10 (0.00)	16 (0.00)	8 (0.01)	8 (0.01)	9 (0.00)	8 (0.01)
Coefficients						
Farm-plot distance [h ha^{-1}]	0.17 (0.00)	0.14 (0.00)	0.25 (0.00)	0.11 (0.00)	0.24 (0.00)	0.22 (0.00)
Plot size [h ha^{-1}]	-0.05 (0.00)	-0.03 (0.00)	-0.09 (0.00)	-0.07 (0.00)	-0.04 (0.00)	-0.01 (0.00)

Notes: Coefficients of the linear regressions on the three-dimensional surfaces for conventional (conv) and organic (org) production. Stated are the estimates (EST) and the respective standard errors (SE). (1) The coefficient is the same for profits and costs, however, the direction of the effect is inverse (2) impact of integrating livestock in production system, (3) reflects higher labour demands of specific requirements in organic livestock production

5.2.5 Discussion and conclusions

5.2.5.1 Economic performance of conventional and organic farming systems

For any plot sizes and farm-plot distances considered in the study, organic farming remains the profit maximising choice for the case study farms when subsidies grated to organic production are considered. This is in line with previous studies finding higher profits in organic farming (e.g. Hanson et al. 1997; Kerselaers et al. 2007; Nieberg and Offermann 2003). These observations contrasts with the still quite low share of 9% (BMEL 2018) of agricultural land under organic production in Germany. In this context, it should be considered that, first, organic farmers face higher production risks related to quantity and quality (Gardebroek et al. 2010). Second, higher profits for organic systems to a large extent reflect price premiums which depend on access to organic value chains. The latter might, however, not always be given. It has for example been reported in the media that organic dairies in Germany do not award additional delivery contracts, preventing conversion (Landwirt 2020; Welt 2018).

In addition to high price premiums, the higher profits of organic production partly arise from lower costs in crop production, mostly from reduced direct costs and from a lower number of passes over the field with consequences on labour and machinery requirements. Similarly, Mahoney et al. (2007) and Nemes (2009) stress the relevance of lower production costs on the higher profitability of organic production.

The labour requirements of organic crop production are lower for most crops. However, the often necessary switch to a more diversified crop rotation can also introduce labour intensive crops as observed on our arable case study farm. The high labour requirements in livestock production of organic farming additionally provoke higher total labour requirements for all three case studies. This fits the findings of previous studies, revealing that organic farms face higher labour requirements per hectare and are managed more labour intensive (Delbridge et al. 2013; Jansen 2000; Offermann and Nieberg 2000; Reissig et al. 2016). Finally, without considering subsidies granted for organic production the profit of the arable and the dairy farm decrease with conversion. This stresses the high relevance of subsidies to overcome income losses associated with the uptake of ecological approaches.

5.2.5.2 Impact of effects of plot sizes and farm-plot distances on conversion decision

The results of the study show the expected direction of the effects of plot sizes and farm-plot distances: larger plot sizes increase economic performance by reducing labour requirements and costs associated with crop production. In contrast, growing farm-plot distances drive up costs and labour requirements. Similar economic effects of plot sizes and farm-plot distances have been found for different regions (Latruffe and Piet 2014; Looga et al. 2018; Lu et al. 2018). Higher effects of plot sizes and farm-plot distances are found in conventional farming systems. This implies that costs savings from large plot sizes and small distances are stronger for conventional farms while adverse effects of small plots and large farm-plot distances are lower for organic farming systems. Nonetheless, independent of the plot size and the farm-plot distance, the profits are higher under organic production for our case studies of farms which converted recently to organic farming. This selection bias renders its likely to find a positive effect on profits, compared to analysing a sample of farms staying in the conventional system. Nevertheless, the economic benefits of conversion increase with decreasing plot sizes and increasing farm-plot distances. It can hence be concluded that incentives to switch to organic production are stronger in landscape settings where plot sizes are limited and joining plots to larger fields is hard. Further, organic farms have advantages when putting bids on smaller plots farther away from the farms.

Currently, organic farming is unevenly distributed within Germany. Organic farming systems are more frequent in regions characterised by lower production intensities and greater land fragmentation (BMEL 2018; Früh-Müller et al. 2019; Petersen et al. 2020; Schmidtner et al. 2012).We shed light on the last factor: potential profit gains from switching to organic production are smaller on large plots and short farm-plot distances. In contrast, economic benefits of conversion are higher for farms operating in more fragmented land markets. It can thus be concluded that regional conversion rates are influenced by present spatial structures and plot sizes and farm-plot distances contribute to the spatial concentration of organic farms, which might motivate regionally differentiated subsidy rates. Land fragmentation thus impact economic considerations of the farmers conversion decision and accordingly add new factors to the wide discussion on conversion (Kallas et al. 2010). Our results thus can contribute to a better understanding of the adaption of organic farming and a more targeted promotion of organic farming systems.

5.2.5.3 Implications on policy and research

The aim of Germany's National Sustainable Development Strategy is to increase the share of organic farming to 20% of the productive agricultural land by 2030. A body of literature discusses the question of whether the expansion of organic farming should be spatial evenly distributed or whether a concentration on certain locations or regions is favourable, c.f. (Taube et al. 2006). In intensive production areas, converting to organic farming can significantly improve environmental conditions (Früh-Müller et al. 2018). However, this requires higher subsidies to reflect differences in opportunity costs of conversion. The effects of plot sizes and farm-plot distances additionally reduce economic benefits of organic agriculture in intensively managed, low fragmented regions. This reinforces the need for higher incentives to overcome income losses associated with the uptake of ecological approaches. This stresses the importance of the farm and market context in the effectiveness of subsidies.

The study is conducted based on case study analysis, giving first insights into the differentiated effects of plot sizes and farm-plot distances on the economic performance of conventional and organic farms. Clearly, a larger sample of farms from different regions is needed to generalize our findings. This is hampered by two important data limitations. First, as underlined by our case studies, switching from conventional to organic farming affects a farm in many aspects. An isolated analysis of the effects of plot sizes and farm-plot distances, as done in this study, requires observations before and after conversion, with detail in farm management. Such observations are quite scarce in existing single farm records such as the Farm Accountancy Data Network (FADN). Second, an integrated analysis of the effects using large samples requires data on actual plot size and farm-plot distances of farms. However, data on land fragmentation are currently not part of official statistics (e.g. FADN and Farm Structure Survey).

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5.2.7 Appendix: Supplementary material

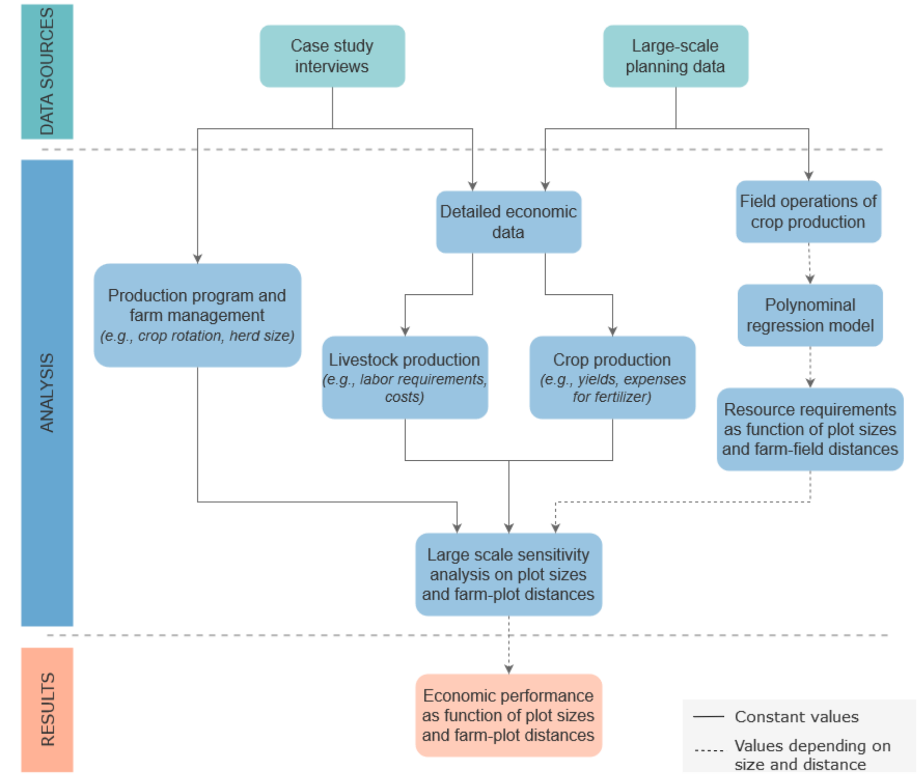

Figure 1: Overview of methodological approach

5.3 The impact of agri-environmental and climate measures on sustainable farm performance – a German case study analysis (UBO)

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5.3.1 Introduction and description of case study region

The European and German agricultural policy strives to reduce negative environmental externalities linked to agricultural production and to foster sustainable, environmentally sound agricultural practices. Under the second pillar of the Common Agricultural Policies and within the frame of the European Agricultural Fund for Rural Development EU member states can implement agri-environmental and climate measures (AECM). AECMs promote the uptake of farming practices which have a beneficial effect on the environment and climate, and go beyond legal and official requirements. The implementations of AECM by farmers are voluntary and subsidies compensate for associated additional costs and related income decreases. The measures aim to protect natural resources and to preserve biodiversity and landscapes, and to reduce burdens that have arisen in the past (EC 2019; Umweltbundesamt 2021).

In Germany, measures that are eligible according to AECM and the level of funding are designed and implemented by the federal states. In the federal state of North-Rhine Westphalia (NRW), these measures include for example diversified crop rotations, extensive use of permanent grassland, cultivation of catch crops and the creation of buffer and flower strips. In 2019, more than 250.000 ha were devoted to AECMs, accounting for about 15% of the agricultural area in NRW (LANUV 2020; MULNV NRW 2020). This study analyses the economic and environmental impacts as well as the employment effects of selected AECMs in two conventional case study farms in NRW.

5.3.2 Methods and Data

The impact of the introduction of AECMs in conventional farming systems is assessed based on simulation with the highly detailed bio-economic farm-scale model FarmDyn. FarmDyn provides a framework to simulate economically optimal farm-level plans and management decisions, considering technical as well as work-time and financial constraints. In our study, the comparative-static version of FarmDyn is used. FarmDyn simulates material flows and quantifies agronomic and economic as well as environmental and social impacts of AECMs and their trade-off. FarmDyn builds on mixed integer linear programming and is realised in GAMS (Britz et al. 2016). A complete documentation of FarmDyn is available online (Britz et al. 2019).

The impact of the introduction of AECMs is assessed at the level of the whole farm for two case studies. We consider two different farm specialisations by analysing an arable crop farm and a dairy farm located in NRW. Key attributes are reported in Table 2. We define a baseline scenario without the opportunity to participate at AECMs, where both comply with the greening regulation and the German nitrate directive. In the AECM scenario, we consider AECMs and the corresponding subsidies in NRW which relate to catch crops, flower strips and the implementation of diversified crop rotation. The implementation of AECMs aims at encouraging the farms to adapt ecological approaches and to shift the farm towards an environmentally friendly farming system. The impact of the uptake of ACEMs on the farm performance is assessed using common indicators as agreed in the LIFT project:

Table 1: Indicators

Economic farm performance	Environmental performance indicators	Employment performance
Profitability indicators *Partial productivity indicators* *Output and input indicators*	*Ratios of input use* *N and P balances* *Pressure indicators (e.g. N-Leaching)* *LCA-indicators* *Biodiversity indicators*	*Type of work* *Off-farm work* *Leisure time* *Labour distribution over months*

5.3.3 Results

5.3.3.1 Production program

In the baseline scenario without the possibility to participate at AECMs, both farms comply with the greening regulations. The arable farm devotes 5% of its area to idle while the dairy farm implemented catch crop production. After implementing AECMs as voluntary policy measure, both farms introduce 10% of flower strips to the farm. Thereby, flower strips substitute against rape seed production. On the dairy farm, the crop share of winter wheat is additionally reduced. Following a slight expansion of the herd size, the acreage of silage maize slightly extended.

Table 2: Key attributes of the case study farms

	Arable Farm Without AES	With AES	Dairy Farm Without AES	With AES
Farm size	60ha		100ha (60ha arable land, 40ha grassland)	
Livestock			132 dairy cows	133 dairy cows
Crop shares	Wheat (65%) Barley (15%) Rape seed (15%) Idle (5%)	Wheat (65%) Barley (15%) Rape seed (5%) Idle (5%) Flower strip (10%)	Wheat (56%) Silage maize (36%) Rape seed (8%) Catch Crops (17%)	Wheat (53%) Silage maize (37%) Flower strip (10%) Catch crops (17%)

5.3.3.2 Economic performance

Table 3 shows that for both farms, participation in AECMs is increasing the profit considerably. A decrease in sale revenues is compensated by a decrease in variable costs and the additional subsidies. Thereby, the share of subsidies on profits increases from 39% to 51% and from 17% to 20% on the arable and dairy farm respectively. Capital requirements remain quasi constant.

Table 3: Supportive economic indicators

In 1.000 €	Arable Farm Without AES	With AES	Dairy Farm Without AES	With AES
Profit	46	49	181	185
Premium	18	25	30	37
Sale revenues	103	95	473	466
Variable costs	63	59	206	203
Capital	13	13	116	117

Figure 1 shows the calculated profitability of the two case study farms. When subsidies are considered, the profitability of the two case study farms increases not only marginally with the implementation of AECMs. The increase is stronger when remuneration of owned production factors (imputed interest, labour and rent) is not considered. Without the consideration of subsidies, the profitability of both farms decreases, as expected.

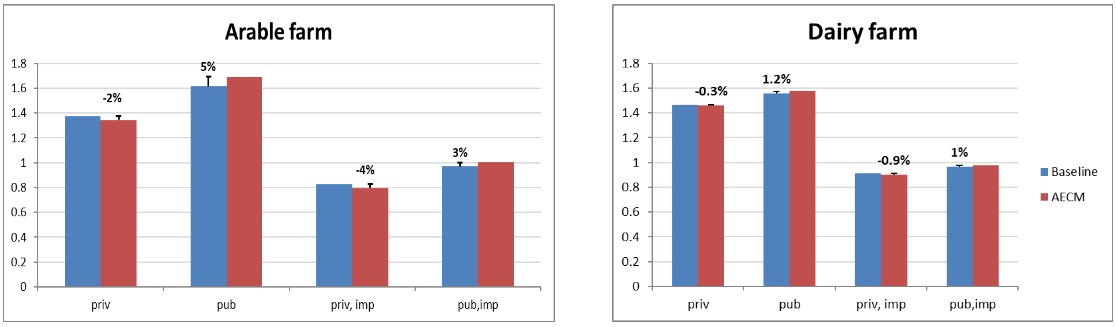


Figure 2: Private and public revenue cost ratios, with and without the consideration of remuneration of owned production factors

The partial productivity is calculated for four different inputs: land, labour, capital and costs of intermediate inputs (Figure 2). On the arable farm, for all inputs, partial productivity increases with the implementation of AECMs. This not only reflects increased profits, but also a decrease of on-farm labour and intermediate inputs. On the dairy farm, a large share of revenues and costs is devoted to livestock production which is not affected by the AECM on arable land, reducing the size of the overall effects. In addition, the slight increase in herd sizes increases input requirements in livestock production. This reflects labour saving effects from the AECMs in crop production. Still, the productivity for all inputs increases with the implementation of AECMs.

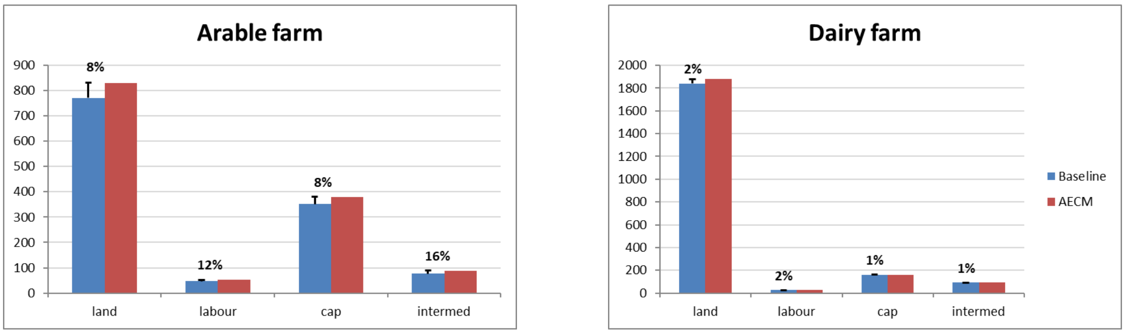


Figure 3: Partial productivity for land, labour, capital and intermediate inputs

5.3.3.3 Social Performance (Labour requirements)

We find labour requirements in crop production decreasing with the introduction of AECMs (Table 4). On the arable farm, the introduction of flower strips mainly substitutes against the production of rape seed, associated with higher labour requirements. The reduced labour needs in crop production stipulate more off-farm work. This goes along with slightly reduced leisure time, but reduces labour peaks in certain months (Figure 3).

Table 4: Labour requirements

Labour requirements	Arable Farm Without AECM	With AECM	Dairy Farm Without AECM	With AECM
Crop production	478	443	1274	1245
Farm management	515	512	1575	1580
Herd management			4351	4376
Off-farm work	486	575		
Leisure time	1041	990	1440	1440

Likewise, labour requirements in crop production on the dairy farm are reduced with the participation in AECMs. Flower strips substitute against labour intensive rape seed and winter wheat production. The reduced labour requirements in crop production allow for a slight increase in herd size. This results in a slightly more even distribution of labour demands over the year, as labour requirements decrease in months with high labour needs in arable production and increase in months where labour is mainly used in livestock production.

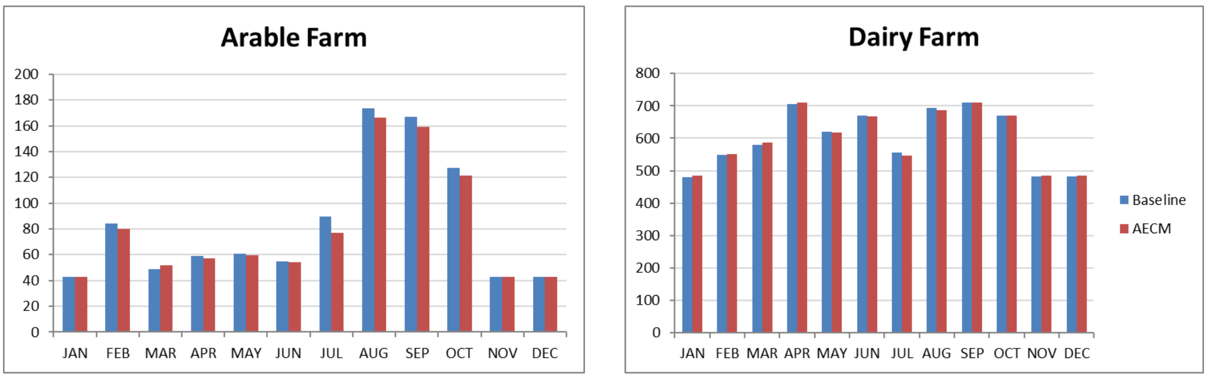


Figure 4: Distribution of on-farm work over month

5.3.3.4 Environmental farm performance

The introduction of AECMs results in a considerable decrease in input requirements on both farms (Figure 4). The substitution of rapeseed by flower strips reduces the nutrient and pesticide requirements per hectare. On the dairy farm, a slight expansion of the herd size provides additional organic nutrients, which helps to substitute mineral fertilisers but increases the costs of bought feeds at farm level. Compared to the arable farm, the dairy farm requires a lower level of pesticides per hectare and relies less on mineral fertilisers.

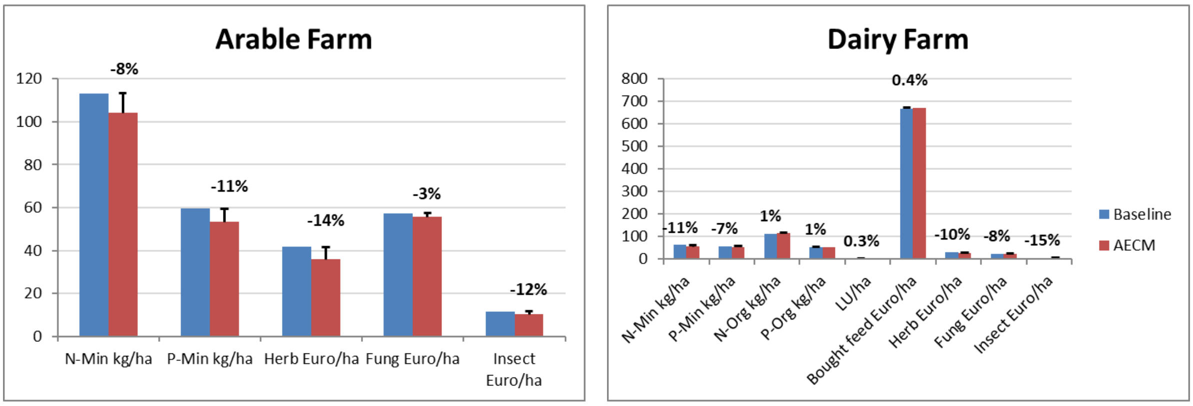


Figure 5: Ratios of input use per hectare

The conversion to a more extensive crop mix due to the integration of flower stripes combined with the reduced application of mineral fertilisers results in an improvement of pressure indicators (Figure 5). First, we observe a slight reduction of phosphorus erosion. On the arable farm, nitrogen leaching considerably decreases with the introduction of AECMs. In contrast, the improvement in nitrogen leaching is smaller on the dairy farm, the overall level being however substantially lower. The humus balance of both farms is negative. With the introduction of AECMs the humus balance improves as less harvested products are removed.

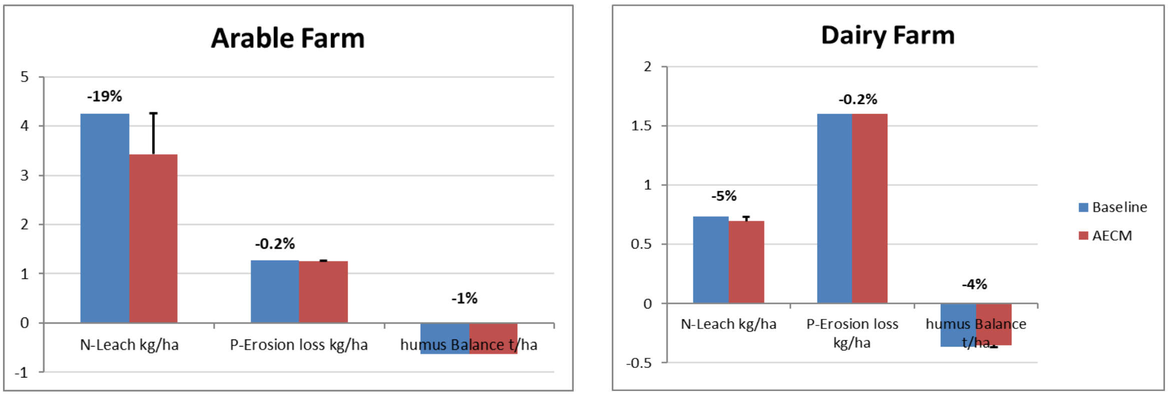
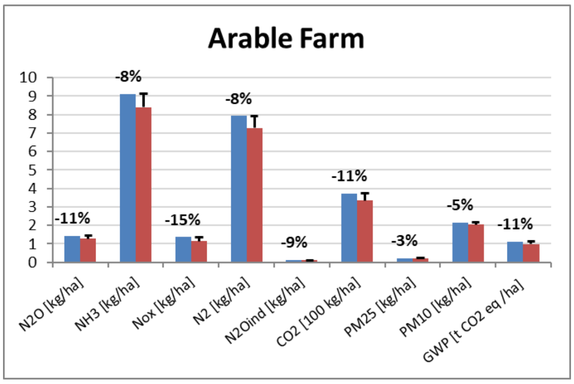


Figure 6: Pressure indicators

In addition, a life cycle assessment is performed, determining yearly emissions of the farm including different pollutants, such as greenhouse gas emissions, nutrient as well as particulate matter emissions. Thereby, emissions linked to intermediate inputs are considered. On the arable farm, the implementation of flower strips results in a considerably reduction of emissions (Figure 6). The effects on greenhouse gases result in a decrease of the global warming potential by 11%. Emissions of ammonia and further nitrogen oxides are reduced by 8% and 15%. Further, particular matter ($PM_{2.5}$ and PM_{10}) emissions decline by 3% and 5%, respectively.

The emissions of the dairy farm mostly relate to livestock production, strongly reducing the size of the analysed effects compared to the arable farms. The small increase in herd size results in slight increase in methane (CH_4) emissions. Thus, even though CO_2 and N_2O emissions are reduced by 10% and 2% respectively, the decrease in the overall global warming potential is quite small at 0.2%. The emissions of particular matter are reduced by 0.5% and 4% ($PM_{2.5}$ and PM_{10}), however, the emissions of total suspended particles (TSP) slightly increase by 0.5%.



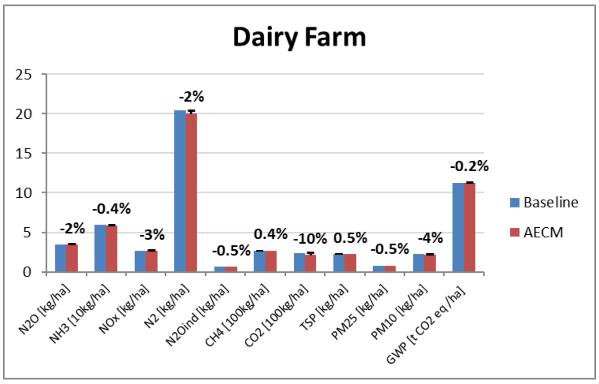
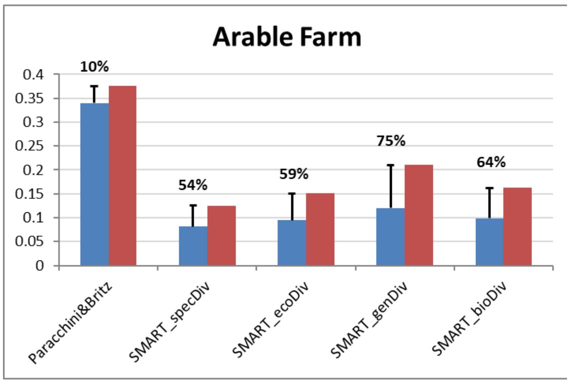


Figure 7: LCA indicators

Finally, the effect of AECMs on biodiversity is assessed using three different indicator frameworks (Weber et al. 2021): the Paracchini & Britz framework (Paracchini and Britz 2010), the SMART index (Schader et al. 2016) and the SALCA method (Jeanneret et al. 2009). On the arable farm, all three frameworks suggest a distinct increase in contributions of the biodiversity, respectively a reduction in farming practices which are harmful to biodiversity (Figure 7). While the indicator of Paracchini and Britz (2010) indicator increases by 10% with the introduction of flower strips, the changes of the SMART indicators are considerably higher. The species, ecological and genetic biodiversity of the SMART framework increase by 54%, 59% and 75%, respectively, resulting in a 64% increase in the overall biodiversity. According to the highly detailed SALCA framework, the implementation of flower strips has a particularly beneficial effect on grasshoppers and butterflies. In contrast, the effect on small mammals and ground beetles is rather limited. Overall, the level of biodiversity increases by 10% in the SALCA framework.



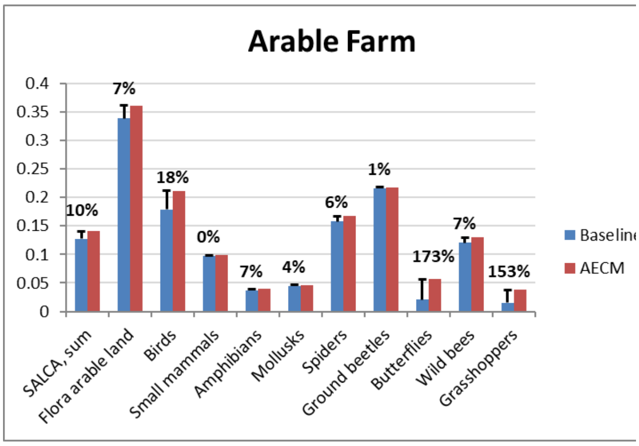


Figure 8: Biodiversity indicators of the arable farm

Similar effects on biodiversity are observed with the introduction of flower strips in the dairy farm (Figure 8). According to the Paracchini & Britz and the SMART framework, the biodiversity of the farm increases by around 5%. Similar to the arable farm, the SALCA index reveals that the introduction of flower strips is beneficial to a diverse group of species, resulting in an overall increase of biodiversity of 6%. According to the SMART and the SALCA frameworks, the dairy farm shows a generally higher level of biodiversity compared to the arable farm. This is partly due to the high proportion of grassland. Although the relative effect is higher for the arable farm, the changes in indicators are similar in absolute terms in both farms.

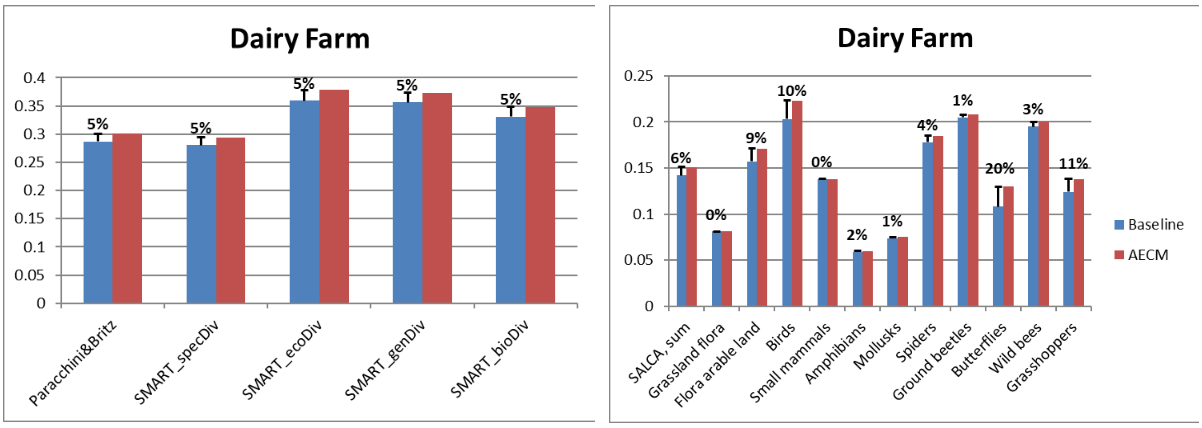


Figure 9: Biodiversity indicators of dairy farm

5.3.4 Discussion and conclusions

This study assesses economic, environmental and employment effects associated with the implementation of AECMs on two case study farms in Germany. By analysing an arable and a dairy farm we address effects of different farm specialisations. The implementation of AECMs as voluntary policy measure induces both farms to introduce flower strips and thus, to extensify their crop rotations. The economic as well as environmental sustainability of both case study farms improves while the application and dependency on external inputs, such as mineral fertilisers and pesticides, in crop production is reduced. The use of external inputs and the environmental impact as well as economic parameters of the dairy farm mostly relate to livestock production, which leads to an overall lower impact compared to the arable farm.

The extensification of arable cropping reduces labour requirements in crop production and reduces labour peaks in months with high labour requirements in arable production. On the arable farm, the released time is used for off-farm work, while on the dairy farm the herd size is expanded. This reduces the beneficial effects of AECMs on the environmental status in the dairy farm. Our results confirm that AECMs, as intended, can foster the adaption of ecological approaches and shift the farm towards an environmentally friendly farming system. Results suggest that the size of these effects depends on the farm type. However, the improvements in environmental status are accompanied by an increased dependency on subsidies and a reduced production of cash crops as a source for food, feed and fibre.

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5.4 The impact of European policies on the uptake of ecological approaches – legume production on dairy farms challenged by European policy interaction (UBO and INRAE)

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5.4.1 Introduction

By shifting the farm towards low input production, increased legume production can be assimilated to an ecological approach. First, legumes can substitute for protein-rich meals as feed, limiting the imports of crops associated with the loss of natural habitats (Sasu-Boakye et al., 2014). Second, as legumes can fix atmospheric nitrogen (N), they can limit the use of synthetic N fertiliser, and thus reduce greenhouse gas (GHG) emissions (Peoples et al., 2009). Third, they regulate pests by breaking the cycle of weeds and diseases, leading to reduced pesticide application (Angus et al., 2015; Nemecek et al., 2008). However, legume production is still low in the European Union due to low profitability at short term and high transaction costs (Jouan et al., 2019).

Since 2014, European member states can establish Voluntary Coupled Support (VCS) for legumes under Pillar I of the Common Agricultural Policy (CAP). France introduced VCS for legumes, reaching 145 million euros in 2017 (European Commission, 2017), but Germany did not. This might explain why the French area of legumes nearly doubled between 2013 and 2017, reaching 3% of UAA, but only increased by 35% in Germany. Interestingly, the share of legumes in arable land in France is half as large in regions specialised in livestock production compared to regions specialised in arable crops (Eurostat, 2018). This may be due to the French implementation of the Nitrates Directive (latter called "French ND") (91/676/CEE), which prohibits manure application on most legumes, discouraging their production on farms with high stocking densities (Caraes, 2018). The German implementation of the Nitrates Directive (latter called "German ND") allows the application of manure on legumes as long as the mandatory N fertilisation planning at farm scale is respected.

This study aims at assessing the impacts of key policy measures affecting legume production on the uptake of legume production in Europe: VCS for legumes and the national implementation of the ND. By covering important agri-environmental legislation policies relating to switches in farming systems and analysis subsidy rates for individual crops to foster more extensive farming practices this study follows scenarios proposed in Milestone 13 (Britz, 2019). By including various environmental and economic indicators, our focus is set on the impacts on the sustainable farm performance. In particular, the interaction between these measures is addressed, since VCS aims at fostering legume production, whereas the ND can potentially constrain it by regulating N supply. By comparing in detail a French and a German representative case study farm different farm, economic and legislative contexts are considered. Further, by conducting a sensitivity analysis on different input and output prices, the policy impact is assessed in different economic contexts. We employ the bio-economic programming farm-scale model FarmDyn (Britz et al., 2014), to quantify agronomic, economic and environmental impacts of increasing legume production.

5.4.2 Description of case study region

We analyse as case studies one French and one German intensively managed dairy farm located in Pays de la Loire (PDL) in France and North Rhine-Westphalia (NRW) in Germany (Table 1). These two regions are characterised by intensive livestock production under temperate climate. The dairy farms were chosen as they combine salient features for the analysis: high quantities of manure produced per ha of land; the possibility of using both grain and forage legume as feed; and compared to pig farms, more constrained feed choices linked to structural characteristics of the farm (e.g., part of fodder area).

Table 1: Description of the dairy farms implemented in the FarmDyn model

	French farm	German farm
Arable land (ha)	49	60
Grassland (ha)	27	20
Number of dairy cows	62	75
Stocking rate (cow.ha^{-1})	0.82	0.94
Breed	Holstein	Holstein
Milk yield (kg.cow^{-1}.year^{-1})	8,600	8,800
Crops	Grassland, wheat, silage maize	Grassland, wheat, silage maize

5.4.3 Method

FarmDyn is a highly detailed bio-economic farm scale model, building on mixed integer linear programming. It provides a framework for the simulation of economically optimal farm-level plans and management decisions, as well as related material flows and environmental indicators. FarmDyn maximizes the farm net present value under various constraints. A complete documentation of FarmDyn is available online (Britz et al., 2019). In our study, the comparative-static version of FarmDyn is used. FarmDyn maximizes the farm net present value under (1) the farms' production feasibility set, (2) working-time and (3) liquidity constraints, and (4) environmental and policy restrictions. In our study, the comparative-static version of FarmDyn is used. The machinery pool used for the necessary field operation to grow legumes is already available, as it is also required to manage the observed benchmark crop rotation and investment costs in buildings and machinery are annualised.

Mathematical programming models represent a valuable tool to analyse technical changes or the introduction of (new) crops, as they describe in detail farm management and investment decisions (Britz et al., 2012; Jacquet et al., 2011). Bio-economic models quantify both economic and environmental indicators and their trade-off by accounting for joint production of agricultural outputs and environmental externalities (Janssen and van Ittersum, 2007). At farm scale, bio-economic models have the advantage of simulating in detail the decision-making process of the farmer, considering technical as well as work-time or financial constraints. This explains their frequent use in European policy impact assessments (Reidsma et al., 2018).

We studied scenarios at the farm scales where the farm types chosen introduce extensification steps, i.e., increase their production of legumes (Britz, 2019). We define a baseline scenario (VCS0) with no VCS for legumes and the national implementation of the ND on each farm: the case study farms are thus conventional farms complying with the greening regulation. By increasing the legume production, we aim at shifting the farm towards low input production. In the first scenario (VCS100), we implement a VCS for legumes in both countries, keeping the national implementations of the ND. This allows to assess the impact of VCS under different legislative contexts. Even though the total VCS budget for legumes is stable among years in France, the VCS per hectare depends on the legume variety and on the total area of legume cultivated during the year. Therefore, we implemented the minimum level established in France: 100 €.ha^{-1} for peas, faba beans and alfalfa. In the second scenario (VCS100ge), the German ND is additionally introduced on the French farm. Lastly, we define a set of scenarios where the VCS per hectare is increased on both farms in increments of 10%, starting from 110 €.ha^{-1} to 300 €.ha^{-1} (VCS110 to VCS300), under the French or the German ND on the French farm, and the German ND on the German farm.

In order to get a first impression on the impact of the uptake of ecological approaches on the economic and environmental farm performance, the study at hand was conducted at the beginning of the project period. At this stage, the LIFT farm typology has not yet been developed and a classification of the case study farms as well as the policy measures according to their degree of ecological approaches could not be conducted in consistent manner to the project. Also, at the time the study was conducted, common indicators of farm performance had not yet been agreed upon.

The main indicators included in our study are:

- Total farm profit
- Contribution of subsidies (i.e., VCS) to profit
- Low input indicators:
    - Protein self-sufficiency
    - Input quantity of mineral fertiliser and manure
- Additional environmental indicators:
    - Global warming potential (GWP) of the farm
    - Indicator of nitrogen leaching (latter called “N leaching”)

5.4.4 Data

In the framework of this study, three legumes are implemented to the FarmDyn model: peas, faba beans and alfalfa (Table 2),allowing the introduction of leguminosae crops in the existing conventional farms (Britz, 2019). Data on yields and on input and output prices for legumes and other crops are extracted from public statistics and professional agricultural press) (AMI, 2019; French Ministry of Agriculture, 2018; IFIP, 2017, p. 2017; IT.NRW, 2019; KTBL, 2009). German input prices for three legumes and concentrated feed are calculated by taking the buying prices for wheat and soybean meal as a basis to determine their value as animal feed, following the method available at DLR Westerwald Osteifel (2011). Peas and faba beans can either be used as feed or sold as cash crops, while alfalfa can only be used as feed. Overall, acquiring data on the input price, whether soybean meal or legumes, was our main difficulty since there is no public database on this subject. An innovative project at the European scale could therefore be carried out to compensate for this lack.

The effectiveness of implementing VCS for legumes and spreading manure on these crops is assessed in different economic contexts: based on a sensitivity analysis different price levels are considered. It covers the selling price of wheat and the buying prices of soybean meal and of three concentrated feeds as the main substitutes for legumes (Charrier et al., 2013). For each tested policy scenario, 1,000 price samples are randomly drawn out of calculated price ranges using Latin Hypercube sampling. Thereby, the correlation between the prices from the observed price series are considered (Eurostat, 2019). For each price sample, FarmDyn simulates the optimal farm-level plan by maximising the net present value. The sampled results are used in a descriptive statistical analysis to determine the performance of key indicators under the considered price ranges.

Table 2: Characteristics of legumes implemented in the FarmDyn model

		Alfalfa	Faba bean	Pea
Yield ($t.ha^{-1}$)	France	10.2	3.0	4.1
	Germany	8.5	4.2	4.7
Selling price ($€.t^{-1}$)	France	-	208	212
	Germany	-	177	198
Buying price ($€.t^{-1}$)	France	-	270	246
	Germany	-	297	306
N from mineralisation of residues (kg $N.ha^{-1}$)	France	25	30	20
	Germany	20	10	10

5.4.5 Results

5.4.5.1 Legume shares and manure spreading

In the baseline scenario (VCS0), both farms produce legumes to comply with the EFA requirement: they represent 5% of the arable land on both farms (Table 3). When the VCS per hectare gradually increases from 100 $€.ha^{-1}$ to 300 $€.ha^{-1}$, the legume share continues to increase (Figure 1). On the French farm, under the French ND, the legume share grows consistently until it reaches its maximum of 34% of arable land in VCS260: at this stage, the need to distribute all the manure prevents further increases of grain legumes on which manure application is prohibited. However, under the German ND where manure can be distributed also to grain legumes, the overall legume share is higher and reaches 45% of arable land in VCS300. On the German farm, the legume share slowly increases to reach a maximum of 28% in VCS300 (Figure 1). As on the French farm, grain legumes (faba bean) substitute for wheat at quasi-constant maize production. The lower increase on the German farm is mainly due to the high prices and yields of wheat, which increase the opportunity costs of legumes.

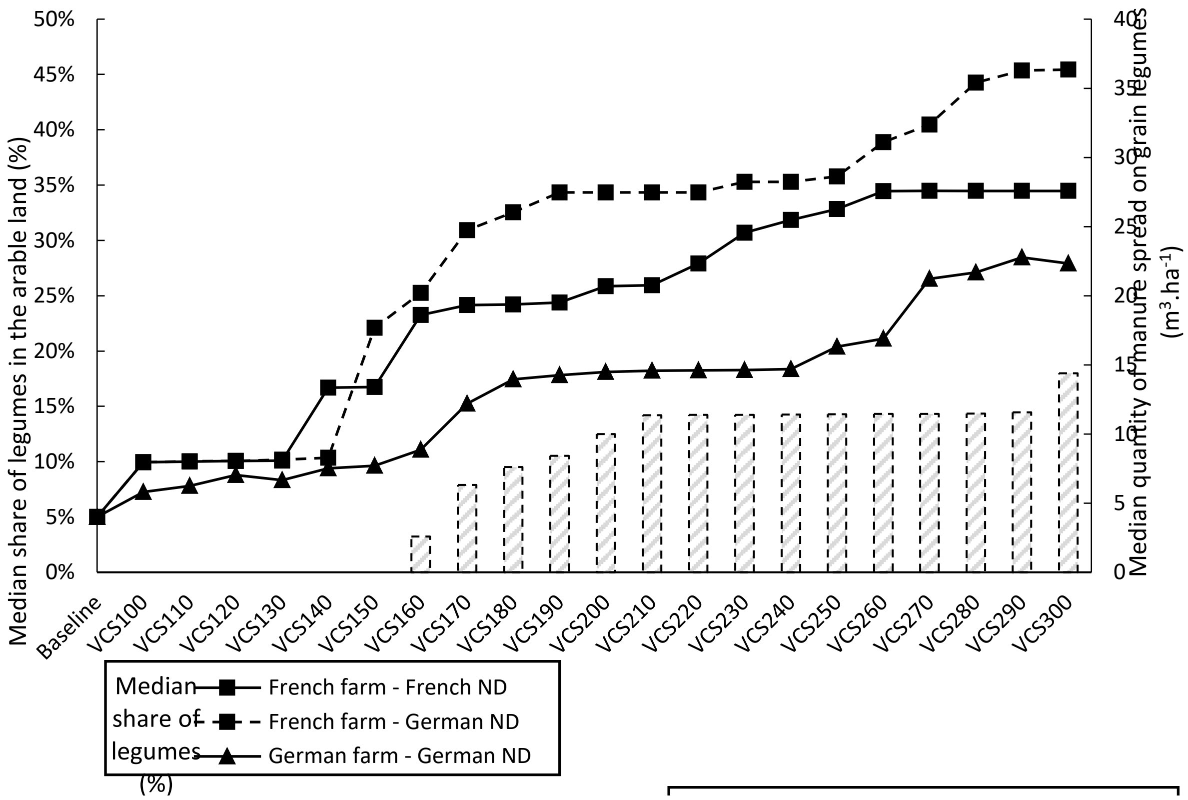

Figure 1: Share of legumes and quantity of manure spread on grain legumes (medians), per farm and implementation of the Nitrates Directive (ND), under the Voluntary Coupled Support (VCS) scenarios for legumes

5.4.5.2 Input use and protein self-sufficiency

The increase in legume production decreases the use of two major inputs. First, legumes produced on the farm substitute purchased feed and thus increase the farms protein self-sufficiency (Figure 2): from 67% to 71% on the French farm under French ND, and to 74% under the German ND. On the German farm, the increase in protein self-sufficiency is particularly high: from 60% to 71%. On both farms, most legumes are used as feed and are not sold to the market. This reveals a better profitability of legumes as intermediate goods (i.e., own-produced feed) than as final goods (i.e., cash crops).

The second input saving effect is related to synthetic N fertiliser. Under VCS300, its use is reduced by 73% and 81% on the French farm, respectively under the French and the German ND, and by 66% on the German farm compared to the baseline scenario. This reflects that legumes provide N and that the overall demand for N is lower as less wheat is produced, a crop with high N need.

Economic and environmental farm performance

The increase in the legume share leads to a slight improvement in environmental indicators on both farms (Figure 2), which partly reflects the associated decrease in input use. On the French farm, reductions in N leaching differ between the two NDs. Under the French ND, N leaching decreases almost continuously to reach a maximal decrease of 16% in VCS300, whereas, under the German ND, it decreases only by 5%. This gap is due to the spreading of manure on grain legumes, provoking their over-fertilisation and thus, additional N leaching. The GWP decreases by 5% in VCS300 under the French ND and by 2% with German ND. The lower decrease under the German ND reflects two factors: higher input purchases and a higher production of alfalfa that causes emissions through the dehydration process.

The profit of the French farm slightly increases by 4%, with a simultaneous rising revenue from VCS under both NDs. However, the total VCS allocated under the German ND is higher than under the French ND (as the legume share is higher). The share of VCS at the farm profit is thus higher under the German ND, reaching 7.4% compared to 5.7% under the French ND in VCS300. Since the simultaneous decrease in GWP is lower, the GWP abatement costs diverge widely between the NDs: under the French ND, they reach 26 €.tCO_2eq in VCS100 and 130 €.tCO_2eq in VCS300, while under the German ND, they reach 190 €.tCO_2eq in VCS100 and 1,040 €.tCO_2eq in VCS300.

On the German farm, the improvement in environmental indicators is similar. N leaching decreases by 5% under VCS300 and GWP by 7%. At the same time, the farm profit slightly increases by 3%, the share of VCS on the profit reaching 4.4% in VCS300 and thus being lower than on the French farm. Even if the decrease in GWP on the German farm is similar to the decrease on the French farm under the French ND, abatement costs are hence far lower, reaching a maximum of 81 €.tCO_2eq in VCS300 but only 12 €.tCO_2eq in VCS100. At this stage, the abatement costs on the German farm are lower than the prices of European Emission Allowances (observed spot prices in 2019 range between 18 €.tCO_2eq to 30 €.tCO_2eq) (European Commission 2020). On both dairy farms, methane from enteric fermentation is the main source of GWP.

5.4.6 Discussion and conclusions

This study is the first one that assesses the interactions of two key policy measures affecting legume production in Europe: VCS for legumes and the national implementation of the ND. In particular, it addresses the issue of interacting policy measures that, on the one hand, aim to promote legume production and, on the other hand, potentially constrain their production by regulating N supply. In doing so, this study provides an exemplary assessment of how policies influence the uptake of ecological approaches and impact the environmental and economic farm performance. This work is of importance for modelling the switch from conventional to organic farming, as legumes are a cornerstone in organic systems to provide nitrogen (Britz, 2019).

We found that relatively low VCS of 100 €.ha^{-1} represent an effective tool to provoke a first increase in legume production. Although further research is needed to get a wider picture of the impact of such coupled support, this finding is in line with the recent study of Cortignani and Dono (2020) who investigate levers to develop rotation with legumes as part of the next CAP. However, medium to high VCS must be implemented to reach the shares of legumes targeted in the study of Cortignani and Dono (2020), which raises questions in terms of economic efficiency of VCS. Thus, we recommend a combination with other measures that lower the opportunity costs of legumes in order to foster their production. In particular, implementing a tax on N synthetic fertiliser to internalize their negative externalities might be an interesting option to promote legume production on farms (Henseler et al., 2020).

Our study shows that large legume shares induced by high VCS do not lead to substantial environmental benefits in the analysed dairy farms. This provides a complementary picture to most other studies that focus on legumes on arable farms. Our findings suggest that the impacts of crop diversification on environmental sustainability of livestock farms is limited. However, the inclusion of other indicators, in particular indicators oriented toward biodiversity, might revise this conclusion. The limited impacts reflect that a large part of the externalities analysed in this study are related to the herd itself: nitrogen leaching and emissions from manure handling, and enteric fermentation represent the main source of climate-relevant emissions. This suggests more ambitious agro-environmental measures that directly target animal production, such as stricter regulations in terms of livestock density or manure handling.

Similarly, other current policies, such as Greening, seem also to reach limited results in terms of improved environmental status (Gocht et al., 2017). In these views, the Green Deal may represent a unique opportunity to improve the sustainability of this essential economic sector (Peyraud and MacLeod, 2020).

Depending on the level of support and input prices, allowing manure spreading on grain legumes on the French farm, as possible under the German ND, can increase the legume share by up to 7 percentage points. However, it does not lead to substantial improvements of environmental indicators. Thus, this policy change can be justified only by other goals such as improving protein self-sufficiency.

Even if the improvement in environmental indicators is limited, we still observed considerable decreases in N-rich input uses. High levels of VCS combined with the possibility of spreading manure on grain legumes leads to a considerable decrease in the use of synthetic N fertilisers and soybean meal. Notably, reduced imports of soybean and its meal are on the European political agenda in the context of so-called "imported deforestation" (European Parliament 2011; Pendrill et al. 2019). However, existing WTO regulation makes it impossible to directly limit imports of soybean. Initiatives from private stakeholders might instead encourage farmers to grow legumes. For example, the development of certified GMO-free milk, produced from animals fed with legumes produced locally, represents an interesting lever to increase the profitability of legumes as feed, while improving the protein self-sufficiency of farms (Jouan et al. 2020b). However, this innovation must be supported by policies to ease processing of legumes at farm level, such as investments in specific storage and improved sorting (Meynard et al., 2018).

Without the introduction of VCS, the results indicate that both farms produce legumes only to meet the EFA requirement. Here, legumes cannot compete with their main substitutes at farm level: Wheat as output and soybean meal and concentrate as input. However, the results of the sensitivity analysis suggest that the profitability of legume production is highly dependent on the economic context: even without the introduction of VCS high shares of legumes are achieved in certain price contexts. The introduction of VCS for legumes to foster more extensive farming practices increases profitability of legumes, rendering cultivation more independent of the economic context. We deliberately analysed high levels of VCS to explore implications of high legume shares not yet observed in conventional farms. Such legume shares make farm profit more dependent on subsidies, which is a doubtful strategy at a time where high subsidies under the CAP are questioned. Indeed, a considerable increase in the production of legumes on livestock farms requires implementing a set of measures that combine regulatory constraints, couple support and investment aid to sectors promoting these crops such as the emerging sector of GMO-free feed.

Finally, our study concerns two representative case studies in prominent dairy production areas and gives first insights into the interactions of two key policy measures affecting legume production in Europe. Clearly, a larger sample of farms of different types and from different regions is needed to generalize our findings. However, the strength of our analysis lies in the nature of the sensitivity analysis carried out. It considers the market environment of main substitutes of legumes at farm level and thus considers different economic contexts. In addition, it would also be possible to carry out a sensitivity analysis on the yields of legumes, which vary more than those of other crops (Cernay et al., 2015).

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5.4.8 Appendices

Table 3: Results of main indicators (median and range) used in the integrated assessment, for selected scenarios, per farm and implementation of the Nitrates Directive (ND)

	French farm - French ND					French farm - German ND					German farm – German ND				
	VCS0	VCS100	VCS150	VCS200	VCS300	VCS0	VCS100	VCS150	VCS200	VCS300	VCS0	VCS100	VCS150	VCS200	VCS300
Share of legumes	5% (5- 35)	10% (5- 46)	17% (5- 48)	26% (5-49)	34% (5- 59)	5% (5- 48)	10% (5- 49)	22% (5- 53)	34% (5- 58)	45% (5- 63)	5% (5- 44)	7% (5- 45)	10% (5- 59)	18% (5- 59)	28% (5- 62)
Grain legumes	*5%*	*7%*	*15%*	*24%*	*32%*	*5%*	*6%*	*20%*	*33%*	*38%*	*5%*	*5%*	*8%*	*18%*	*26%*
Protein self-sufficiency	67% (58- 86)	69% (58- 89)	71% (58- 91)	71% (58- 92)	71% (58- 92)	68% (58- 90)	68% (54- 92)	71% (58- 92)	71% (56- 92)	74% (59- 92)	60% (54- 88)	61% (49- 89)	61% (54- 90)	65% (49- 91)	71% (54- 92)
Manure on legumes (m^3.ha of legumes^{-1})	0 (0- 10)	0 (0- 15)	0 (0- 15)	0 (0- 15)	11 [a] (0- 15)	0 (0- 19)	0 (0- 20)	0 (0- 21)	10 (0- 21)	14 (0- 21)	0 (0- 14)	0 (0- 14)	0 (0- 20)	0 (0- 20)	0 (0- 21)
Synthetic fertiliser (kg.ha^{-1})	125 (35- 131)	105 (23- 131)	74 (22- 131)	42 (21- 131)	34 (11- 131)	127 (22- 134)	108 (21- 136)	52 (17- 134)	34 (13- 136)	24 (8- 134)	183 (34- 185)	170 (29- 188)	157 (18- 185)	116 (17- 189)	61 (11- 184)
Farm Profit (k€.ha^{-1})	1.13 (1.05 - 1.25)	1.14 (1.07 - 1.27)	1.15 (1.09 - 1.25)	1.16 (1.10 - 1.26)	1.17 (1.13 - 1.26)	1.14 (1.05 - 1.27)	1.15 (1.08 - 1.29)	1.15 (1.09 - 1.27)	1.16 (1.11 - 1.27)	1.18 (1.14 - 1.27)	1.39 (1.25- 1.64)	1.39 (1.27- 1.61)	1.40 (1.29- 1.63)	1.41 (1.31- 1.62)	1.43 (1.34- 1.63)
Share of VCS in profit	0.0% (0- 0)	0.6% (0.3- 2.4)	1.4% (0.4- 3.7)	2.9% (0.6- 5.0)	5.7% (0.9- 9.1)	0.0% (0- 0)	0.6% (0.3- 2.5)	1.9% (0.4- 4.0)	3.8% (0.6- 5.8)	7.4% (0.8- 9.6)	0.0% (0- 0)	0.4% (0.3- 2.1)	0.8% (0.4- 4.1)	1.9% (0.6- 5.5)	4.4% (0.8- 8.5)
N leaching (kgN.ha^{-1})	36 (22-41)	36 (19-41)	36 (19-41)	35 (19-41)	30 (18-41)	36 (20-39)	36 (19-42)	34 (19-48)	34 (19-48)	34 (17-52)	20 (7-23)	19 (7-23)	19 (6-31)	19 (6-32)	19 (6-36)
GWP (kgCO2eq.kg milk^{-1})	1.25 (1.06 - 1.69)	1.21 (1.04 - 1.69)	1.21 (1.03 - 1.69)	1.20 (1.02 - 1.69)	1.16 (1.01- 1.65)	1.23 (1.05 - 1.70)	1.23 (1.04 - 1.81)	1.22 (1.03 - 1.70)	1.22 (1.02 - 1.77)	1.21 (1.02 - 1.68)	1.37 (1.06 - 1.68)	1.30 (1.05 - 1.70)	1.29 (1.04 - 1.71)	1.29 (1.04 - 1.69)	1.26 (1.02 - 1.71)

[a] Manure spread only on alfalfa; The minimum and maximum values are in brackets;

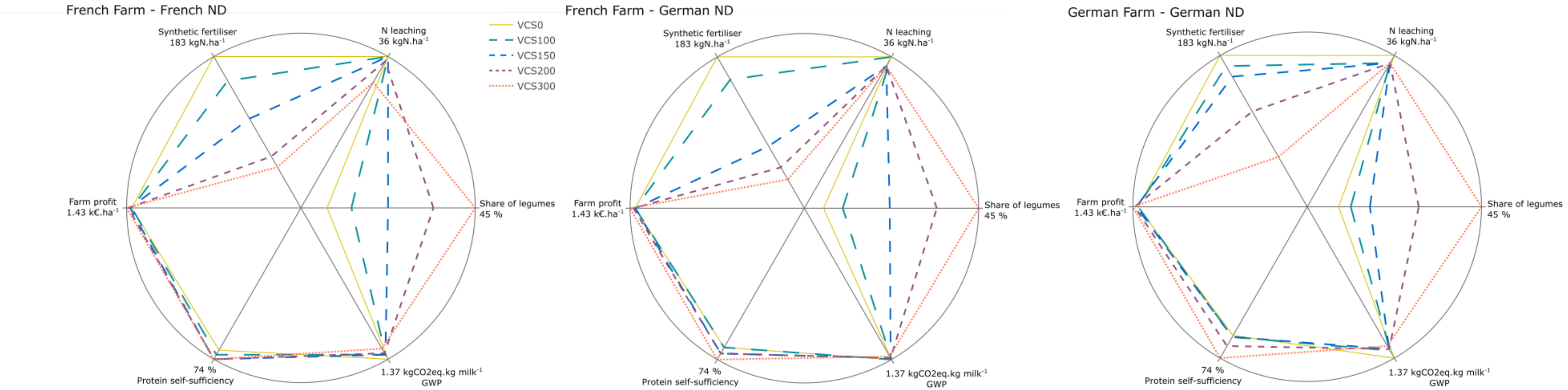

Figure 2: Integrated assessment of farms, across specific scenarios and Nitrates Directive (ND) implementation.

The chart compares economic and environmental indicators across different levels of VCS for each farm and implementation of the ND. For each indicator, the upper boundary is defined by the maximum value observed in the study, across all case studies and scenarios. The minimum value is set zero for all indicators.

6 Conclusion

Against the background of the ambitious goal of the EU to achieve an increasing uptake of ecological approaches in its farming sector, assessing the effects of such a transition on the economic viability of and production of food, feed and fibre by farms is of crucial importance. The aim of this deliverable was therefore to assess and compare technical-economic farm performance across the EU depending on the degree of ecological approaches adopted by farms, and explore drivers affecting their performance.

In order to accomplish this, the wide variety of farm types and biophysical, socio-economic and political framework conditions present in the EU, needed to be considered. This required an approach, allowing to consider regional specifics, while still permitting comparisons between different regions and countries. The deliverable thus consists of several academic papers, focussing on a range of different case studies, applying a wide range of methods, which can most generally be divided into empirical econometric or statistical approaches and bio-economic models. At the same time, all academic papers follow a similar structure and include some common elements in terms of the applied methods, in particular a set of common indicators of technical-economic farm performance was implemented in several papers. Various approaches to differentiate farms according to the degree of ecological approaches adopted were explored, including the LIFT farm typology developed in WP1 and other strategies.

Overall, our results show that the wide variety of farm types and biophysical, socio-economic and political framework conditions present in the EU matter: results of comparing technical-economic farm performance depending on the degree of ecological approaches adopted, as well as with respect to drivers of farm technical-economic performance, are heterogenous and vary between the different analyses. The effects of a further increase in the uptake of ecological approaches in EU agriculture on technical-economic farm performance are thus also likely to have heterogenous effects on farms. Nevertheless, our results illustrate some tendencies, visible across several analyses as well. For example, in cases where farms associated with a higher degree of ecological approaches are more profitable compared to more conventional farms, this advantage in profitability is mostly only present, if subsidies are considered. Additionally, farms associated with a higher degree of ecological approaches in most analyses tend to be more productive in their use of intermediate inputs and less productive in terms of most other inputs compared to more conventional farms. However, even these very general tendencies stated here need to be considered with care, as they do not always hold across all case studies.

Results are also heterogenous in terms of drivers of farm performance like possible policy measures, aimed at supporting an ecological transition: for example, the results show mixed effects of subsidies on technical-economic performance on farms with a different degree of ecological approaches. Therefore, this heterogeneity also needs to be considered by policy makers and can most likely best be addressed by providing a policy framework, which provides the necessary flexibility to adjust policy measures to region-specific framework conditions in order to foster economic viability of farms in the context of an ecological transition of EU agriculture.

In the end, economic performance is only one of the considered performance dimensions within LIFT. While some papers in this deliverable have already integrated the technical-economic and environmental dimension of farm performance jointly, private-social performance as well as employment effects at the farm level need to be considered as well, in order to arrive at a holistic assessment of farm performance. Task 5.1 will therefore in a next step undertake an integrative assessment of these performance dimensions, uncovering associated trade-offs and synergies of an increasing uptake of ecological approaches in the EU farming sector. Finally, WP6, in particular Task 6.2 and Task 6.3, will further investigate the role of policies in the development of ecological agriculture.

7 Deviations or delays

None.

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