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Drivers of farm performance

EMPIRICAL COUNTRY CASE STUDIES

Johannes Sauer,

Catherine Moreddu

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Drivers of Farm Performance
Empirical Country Case Studies

Johannes Sauer, Technical University of Munich
Catherine Moreddu, OECD

This report contains an empirical analysis of the productivity and sustainability performance of different types of farms in thirteen countries. Farm productivity performance is measured through estimates of average productivity levels and through annual rates of technical change. Evidence on the environmental sustainability of farm groups is based on an index that reflects environmental pressure per hectare and the local environmental sustainability of production practices. In addition to environmental sustainability, the analysis also considers fundamental differences across farms with respect to farm structure, innovation of operations, individual characteristics as well as farm location. Productivity performance by farm classes is related to the environmental sustainability performance and to other farm characteristics in order to shed light on the factors that drive or impede farm performance. Empirically identifying the main conditions for and obstacles to performance improvement supports the development of effective and efficient policies targeting the performance of farms. This analysis contributes in particular to a better understanding of the synergies and trade-offs between productivity and environmental sustainability performance.

This report provides the results of the cross-country analysis contained in document [TAD/CA/APM/WP(2020)2/PART1/FINAL]. Country specific analysis and supporting tables of Annex D are available in separate documents, respectively [TAD/CA/APM/WP(2020)2/PART2/FINAL] and [TAD/CA/APM/WP(2020)2/ANN/FINAL].

Keywords: Agriculture, productivity, technical change, technology, environmental sustainability, drivers of performance, farm structure, innovation, agricultural policy

JEL Codes: D24, O31, O33, Q12, Q18

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Executive summary

Improvements in farm productivity and environmental sustainability will occur mainly through innovation and technical change, ongoing structural change and more sustainable management of natural resources. Farms in different regions and sectors face specific natural and structural conditions, different market and policy incentives, and hence may use different technologies and practices. As a result, farm productivity and environmental sustainability performance vary widely across time and space.

This analysis of the productivity performance and environmental sustainability of different types of farms aims at empirically identifying the main conditions for and obstacles to sustainable productivity growth, and thus to support policy advice. Recognising farm heterogeneity is at the core of designing effective and efficient policies targeting the performance of farms. This requires in particular a better understanding of the synergies and trade-offs between productivity and environmental sustainability performance.

This report contains an empirical analysis of farm performance across thirteen countries for different farm types. It considers fundamental differences across farms with respect to characteristics such as farm structure, environmental sustainability of production practices, innovation of operations, individual characteristics as well as farm location. Farms are grouped in technology classes, which are defined statistically using a production function based latent-class estimation procedure linked to a principal component analysis. A number of multi-dimensional indices define the farms' characteristics, on the basis of which the estimation procedure groups them into up to four distinct classes. The production technologies and productivity patterns are modelled and evaluated for the different kinds of farms using a flexible functional form, and measures of farm performance are derived.

The empirical analysis provides evidence on the productivity performance of farms in the different technology classes, measured through estimates of Total Factor Productivity levels and through annual rates of technical change. Evidence on the environmental sustainability of farm groups is based on an index that reflects environmental pressure per hectare, as measured by the intensity in fertiliser, chemical or fuel use, by stocking density in the case of livestock, and by the likelihood of adoption of environmentally-friendly practices. Due to data limitations, this index does not include all aspects of sustainability, and does not consider environmental pressure per unit of output.

Productivity performance can then be related to the environmental sustainability performance and to other farm characteristics to shed light on the factors that drive farm performance. For example, the farm structure index reflects the farm physical size in terms of number of hectares or animals, and the reliance on family labour. The innovation-cooperation-commercialisation index reflects investments to purchase new technologies, investment in land, new activities and sometimes the use of practices requiring specific technology, while the technology index aggregates various indicators of capital, labour and material intensity per hectare, per cow, or per worker as relevant.

Results suggest that the farm cases analysed in the thirteen countries use significantly distinct technologies, and have different technical change patterns, both in terms of overall magnitudes and associated relative output and input mix changes. In some cases, high productivity performers also have the highest rates of technical change, suggesting a widening gap between high and low productivity performers. In other cases, the productivity gap between classes is narrowing, as less productive farms have a higher rate of technical change. The potential productivity gains that would occur if farms in the less productive groups were to switch to a more productive technology are generally large. However, natural and human resource constraints may limit the capacity to make that switch.

The empirical analysis suggests that the relationship between productivity and environmental sustainability, as measured by an estimated index of environmental sustainability, which seeks to capture the pressure on the local environment, is mostly negative for dairy, pig and poultry farms. For the ruminant farms studied, the trade-off between productivity and environmental sustainability is less common, and there are also strong synergies in some cases. For crop farms, there are often strong synergies, while the trade-offs that are found are mostly weak.

Some strong evidence for a positive correlation between the innovation-cooperation-commercialisation index and productivity is found at farm level across different production types. Evidence also suggests that the productivity of agricultural operations is positively associated with the size of operations and with the share of hired labour. Innovative farms, which invest in new technologies and develop new activities, are also found to be more likely to achieve high productivity levels. Empirical evidence with respect to farm environmental sustainability is less conclusive: there is little evidence among the sample for a positive correlation between family farming (i.e. operations that depend on own family labour) and environmental sustainability, but in many cases, environmentally sustainable farms are found to be smaller than average. Moreover, evidence suggests that some larger farming operations do produce sustainably (except for pig and poultry farming), indicating that observed trade-offs between size and environmental sustainability do not necessarily imply that larger operations must be less environmentally sustainable. The analysis points to a robust positive correlation between diversification of production and environmental sustainability, and a negative correlation between intensity of input use and environmental sustainability. However, for a better understanding of environmental sustainability performance and its drivers, it would be important to develop farm level indicators that better reflect the multiple dimensions of environmental sustainability. It is also important to bear in mind that local environmental sustainability may not correspond to global environmental sustainability. For example, low input systems may put less pressure on the local environment, but, if productivity is lower, also imply that land elsewhere is brought into agricultural production.

Further work aiming to strengthen the basis for guiding policies could extend the analysis to additional countries and analytical questions, including the potential dynamics in farms' technology class membership over time as well as specific policy responses with respect to individual technology classes given various production settings. Significant improvement in data availability would be required to analyse further the relationship between production intensity and the intensity of environmental pressure.

1. Context and scope

To respond to growing demand for agricultural products, the farm sector around the world needs to accelerate further environmentally sustainable productivity growth. This will occur mainly through innovation and technical change, ongoing structural change and more environmentally sustainable use of natural resources, while also taking account of climate change and the increased likelihood for natural disasters. Farms in different regions and sectors face specific natural and structural conditions as well as varying market and policy incentives, and hence may use different technologies and practices. As a result, farm productivity and environmental sustainability performance varies widely across time and space.

This empirical project is part of OECD efforts to understand the impact of policies and other factors on productivity and environmental sustainability at the farm level. It is implemented in collaboration with the OECD Network for Farm-Level Analysis (FLA).[1] Consequently, country cases considered in the analysis depend on OECD members' voluntary participation in the project in the form of data access and advice. This project links to previous OECD work on productivity growth and dynamics, structural change and farms' clustering as well as innovation behaviour and performance links (Kimura and Sauer, 2015; Bokusheva and Čechura, 2017; Sauer, 2017). It significantly adds to this work by explicitly considering multiple dimensions of farms' performance and characteristics in a statistically robust way.

The aim of the project is to analyse the link between farm characteristics and farm performance in order to understand more adequately farmers' behaviour and responses to different policies. The analysis of the productivity and environmental sustainability performance of different types, categories or classes of farms aims at identifying empirically the main conditions for and obstacles to environmentally sustainable productivity growth. This original comparative empirical perspective is expected to support policy advice. In fact, recognising farm heterogeneity is at the core of designing effective and efficient policies targeting the performance of farms. More specifically, the findings point policy-makers to the characteristics of the lower performance farms. The analysis also identifies synergies and trade-offs between the two dimensions of performance and the different determinants. Policy makers can then decide to incentivise lower performance farms to transition into higher performance classes, to focus policies on further improving the enabling environment for farms that drive the national performance, or to guide high performers into more environmentally sustainable ways for improving productivity.

This report covers thirteen countries, including nine EU Member States (Table 1.1). In total, there are 33 farm cases as the number of farm cases varies among countries from one to seven. The most represented farm types are dairy farms (nine countries) and crop farms (seven countries). The empirical analysis of these cases focuses on the specification and estimation of the different technology, and modelling of farm Class identification, using comprehensive farm level data for several years (see Section 2 on implementation).

This report contains a brief presentation of the methodology and data supporting the empirical analysis (Section 2), which is completed by a comprehensive outline of the empirical methodology in Annex A. Section 3 synthesises country results, while Section 4 summarises and concludes. Annex B contains a comprehensive literature review on state-of-the-art methods for identification and estimation of heterogeneous farm technologies and Annex C contains tables supporting Section 3. The individual empirical results by country are presented in document [TAD/CA/APM/WP(2020)2/PART2/FINAL], and Annex D, which contains descriptive statistics for the farm samples used in each country and the detailed estimation results, is presented in document [TAD/CA/APM/WP(2020)2/ANN/FINAL].

[1] See network website at: www.oecd.org/agriculture/farm-level-analysis-network.

Table 1.1. Country and farm coverage

33 farm case studies

	Crop farms	Rice farms	Small-scale fruit farms	Dairy farms	Cattle farms[1]	Pig farms	Poultry farms	Sheep farms	Wool farms	Mixed crop-livestock farms	Mixed beef-sheep farms
Australia	X			X	X			X	X	X	X
Chile			X								
Czech Republic				X							
Denmark				X		X[2]					
Estonia				X							
France	X			X							
Hungary	X										
Ireland	X			X	X[3]			X			
Italy	X										
Korea		X									
Norway	X			X	X						
Sweden	X			X							
United Kingdom	X[4]			X		X	X			X	
Number of cases	8	1	1	9	4	3	1	2	1	2	1

Note:
1. Also called beef farms.
2. Pig fattening farms and pig rearing and fattening farms.
3. Cattle rearing farms and "cattle other" farms.
4. Cereal farms.
Darker blue indicates the farm case studies (farm types and countries) included in the report.

2. Implementation

2.1. Empirical and econometric framework

Annex A outlines the methodological steps that have been applied to empirically identify and econometrically approximate the different technology classes for each national farm type. Furthermore, it describes the statistical procedure that has been used to represent a variety of farm classes within the number of classes determined empirically based on a combination of differences in multiple farm specific characteristics as well as multiple netput (i.e. output and input) variables (see in more detail Sauer and Morrison-Paul, 2013).

2.1.1. Technology model

The first part of the econometric modelling exercise consists of choosing a technology function to approximate the production process of a farm. The analysis considers a production function model representing the most output producible from a given input base and existing production conditions (representing the feasible production set). The production function is approximated by a flexible functional form (second-order approximation) to accommodate various interactions among the arguments of the function, including non-constant returns to scale and technical change biases. Annex A contains a detailed description of the flexible production function model and discusses further the choice of the approach.

Recognising and evaluating heterogeneity among production systems and exploring differences in technical change developments requires a more explicit approach, consisting of estimating the technology separately for different groups or 'classes' of farms. Hence, the estimation of production technology is combined with a probabilistic approach that allows considering simultaneously multiple characteristics of farms operating in a specific production system. This approach results in an adequate approximation of the individual farm's production technology by considering a multitude of characteristics and therefore robustly identifying various farm groups or classes along these characteristics, for which technologies are then estimated. Hence, the estimation of the production structure is combined with the estimation of a latent class structure.

2.1.2. Class identification model

With regard to the systematic classification of farms based on various characteristics, a latent-class estimation procedure is used to simultaneously estimate production technology and class membership based on different multi-dimensional indices reflecting farm heterogeneity (see methodology in Sauer and Morrison-Paul, 2013).

This results in a separation of the data into multiple technological classes (groups or categories). This separation is based on estimated probabilities of class memberships considering multiple pre-specified criteria. Each farm is then assigned to a specific class based on these probabilities while both the estimated technological (flexible TL function) as well as the estimated probability relationships are considered (Sauer and Morrison-Paul, 2013; Balcombe et al., 2006). Hence, this approach overcomes possible estimation bias due to omitted variables with respect to the Class identification vector. It also effectively addresses endogeneity suspicions by a simultaneous estimation approach (i.e. a technology model and Class identification model). Statistical tests are performed to choose the most adequate number of classes/technologies to be considered. Furthermore, in addition to multiple technologies, a flexible functional form with a random effects panel estimation routine is applied (Greene, 2005; Alvarez and del Corral, 2010) to capture farm heterogeneity over time. In this project the focus is explicitly on measuring productivity instead of unobserved inefficiency (based on a frontier specification) to reflect the specific interest in relative productivity levels between farms considering country level contextual specificities (see also Section 2). Annex A in this report contains a detailed description of the Class identification model.

2.1.3. Multi-dimensional indices

Farms are production units, which differ along multiple characteristics: production structure, environmental impact and environmental sustainability, innovation behaviour, commercialisation focus, openness towards cooperation, input intensity and capital endowment, diversity of production, individual characteristics such as age or education, as well as locational conditions. Multi-dimensional indices consisting of different variables that measure underlying farm characteristics relevant for the dimension of the specific index to approximate are defined to approximate these farm characteristics. They are then estimated statistically, and incorporated as elements of the Class identification vector.

These individual index components can be equally weighted with regard to their importance for the overall index score. The principal components analysis (PCA) is applied as a statistically well-defined and empirically tested multivariate method to estimate significant and robust weights for the indices' components. The PCA is a method to conduct a conceptual factor analysis that will then create statistically robust indices based on different variables (see Annex A for more information on the construction of multi-dimensional indices and the estimation of performance measures).

For subsequent analyses up to seven multi-dimensional indices are defined, subject to data availability, and estimated to identify and measure class membership per farm and year. Table 2.1 provides an overview of the choice of indices' components. The interpretation of these indices is discussed in Section 3.4.1.

Table 2.1. Indices for farm classification

Components for multi-dimensional indices as elements of Class identification vector q, see equation [3] in Annex B

Indices / Components	Index 1 Structure[1]	Index 2 Environmental sustainability	Index 3 Innovation-coop-comm[2]	Index 4 Technology-Intensity	Index 5 Diversity	Index 6 Individual-hum. cap.[3]	Index 7 Location	Index 8 Household	Index 9 Financial
Agricultural area	X								
Age of operator						X			
Agritourism income			X						
Altitude							X		
Biofuel income			X						
Capital per cow				X					
Capital per labour				X					
Chemicals use per ha		X							
Contract farming			X						
Education						X			
Environmental subsidies per ha		X							
Equity/Debt ratio									X
Experience						X			
Family labour share	X								
Female/Male labour share								X	
Forestry production					X				
Fuel per land		X							
Gender						X			
Herd size	X								
Herfindahl index[1]					X				
Household size								X	
Insurance expenditure			X						
Investment subsidies			X						
Labour per cow				X					
Labour input spouse								X	
Land irrigated share			X						
Land rented share			X						
Less-favoured-area							X		
Material per land				X					
Marital status						X			
Natura 2000							X		
Net investment ratio			X						
Nitrate derogation		X							
Number of holdings	X								
Off-farm income								X	
Organic production		X							
Ownership	X								
Part-time farming								X	
Production diversity					X				
Professional fees			X						
Profit monitoring programme			X						

Indices / Components	Index 1 Structure[1]	Index 2 Environmental sustainability	Index 3 Innovation-coop-comm[2]	Index 4 Technology-Intensity	Index 5 Diversity	Index 6 Individual-hum. cap.[3]	Index 7 Location	Index 8 Household	Index 9 Financial
Rural-Urban classification							X		
Soil classification							X		
Professional fees			X						
Stocking density		X							
Tillage area		X							
Total subsidies									X
Total assets									X
Water charges		X							

Note: Final choice of indices' components depends on production type and data availability per country case.
1. The structure index includes variables of the physical size of farm operations (area, herd) and reliance on family labour.
2. Innovation-cooperation-commercialisation.
3. Individual and human capital. This index concerns the characteristics of the farm operators, such as age, education, experience and gender.
4. The Herfindahl Index measures the degree of specialisation based on the sum pf squared output shares.

2.1.4. Full model specifications

The combined (technology and Class identification) model is estimated in a cross-sectional or a panel form whereas for the full-model specification a random effects based estimator is applied (Sauer and Morrison-Paul, 2013; Greene, 2005). The panel data related specification of the model is presented in Annex A.

2.2. Empirical implementation

2.2.1. Measurement and determinants of farm performance

Performance measurement at farm level can consider various dimensions of performance – economic performance, environmental sustainability performance, innovation or even social or cultural performance. Economic performance measures can relate to productivity, profitability, cost-effectiveness, technical or allocative efficiency, or technical change over time in terms of productivity growth. A total factor perspective as in Kimura and Sauer (2015) can be differentiated from a more partial perspective focusing on the performance in the use of specific production factors. Accordingly, quantitative performance measurement at farm level uses either a non-parametric or a parametric method (e.g. a Total Factor Productivity (TFP) index method versus a micro-econometric based average or frontier method).

Given data availability, the analysis below considers average TFP per farm and per year as the main economic performance measure estimated using a micro-econometric production function framework. **The measure of productivity used in this analysis is the potential output levels that could be achieved with a given input bundle.** To make those absolute productivity levels comparable across countries, they are expressed in a common monetary unit, the euro. Technical change, per class and technology is measured by shifts in the overall production frontier over time (see section on performance measures in Annex A for a detailed explanation on measurement of productivity and its components).

Farms' economic performance is the result of various structural, process and behavioural factors. First, the specific production structure related to type and qualification of labour or the relative farm size matters. Further, access to certain resources and technologies (such as natural resources, infrastructure, and extension services) as well as agro-ecologic conditions and climate dynamics (e.g. soil quality, precipitation, biodiversity etc.) play a major role. The location of the farm in terms of market access and policy framework, as well as specific network effects, is also crucial. Finally, in addition to unforeseen events (such as pests, diseases, and natural disasters) individual abilities and characteristics (such as experience, education, age, and peer-group interaction) determine to a certain extent the farm's economic performance. Because of all these factors, farms operate with different production technologies or production systems, which are subject to varying technical change patterns. Moreover, new production technologies or systems may result in a different input-output mix. This may be in the form of a continuum based on discrete changes in technologies or involve an entirely different production frontier (Sauer and Morrison-Paul, 2013).

2.2.2. Example of a model estimated empirically: Dairy farms in Estonia

Given the technology and Class identification model components outlined in the previous section and detailed in Annex A, and considering the available data, the (fully flexible) model is estimated for the Estonian dairy sector in a panel as well as cross-sectional specification, using equation [1] below, which is expressed in natural logarithm (ln). Other country estimation models follow this model using available output and input variables.

$$
\begin{aligned}
lnmilk_{it|c} = {} & \alpha_0 + \beta_{cows,c} lncows_{it} + \beta_{cap,c} lncapital_{it} + \beta_{fod,c} lnfodder_{it} + \beta_{mat,c} lnmaterial_{it} + \\
& \beta_{oth,c} lnother_{it} + \beta_{lbh,c} lnhiredlabor_{it} + \beta_{lbf,c} lnfamilylabor_{it} + \\
& + 0.5 * \beta_{coco,c} lncows_{it}{}^2 + 0.5 * \beta_{caca,c} lncapital_{it}{}^2 + 0.5 * \beta_{ff,c} lnfodder_{it}{}^2 + 0.5 * \\
& \beta_{mm,c} lnmaterial_{it}{}^2 + 0.5 * \beta_{oo,c} lnother_{it}{}^2 + 0.5 * \beta_{hlhl,c} lnhirlab_{it}{}^2 + 0.5 * \beta_{flfl,c} lnfamlab_{it}{}^2 + \\
& + \beta_{coca,c} lncows_{it} lncapital_{it} + \beta_{cof,c} lncows_{it} lnfodder_{it} + \beta_{com,c} lncows_{it} lnmaterial_{it} \\
& + \beta_{co,c} lncows_{it} lnother_{it} + \beta_{cohl,c} lncows_{it} lnhiredlab_{it} \\
& + \beta_{cofl,c} lncows_{it} lnfamilylab_{it} + \\
& + \beta_{caf,c} lncap_{it} lnfodder_{it} + \beta_{cam,c} lncap_{it} lnmaterial_{it} + \beta_{ca,c} lncap_{it} lnother_{it} \\
& + \beta_{cahl,c} lncapital_{it} lnhiredlab_{it} + \beta_{cafl,c} lncapital_{it} lnfamilylab_{it} + \\
& + \beta_{fm,c} lnfod_{it} lnmaterial_{it} + \beta_{f,c} lnfodder_{it} lnother_{it} + \beta_{fhl,c} lnfod_{it} lnhiredlab_{it} \\
& + \beta_{ffl,c} lnfodder_{it} lnfamilylab_{it} + \\
& + \beta_{m,c} lnmat_{it} lnother_{it} + \beta_{mhl,c} lnmaterial_{it} lnhiredlab_{it} + \beta_{mfl,c} lnmaterial_{it} lnfamilylab_{it} \\
& + \beta_{ohl,c} lnother_{it} lnhiredlab_{it} + \beta_{ofl,c} lnother_{it} lnfamilylab_{it} \\
& + \beta_{hlfl,c} lnhiredlab_{it} lnfamilylab_{it} + \\
& + \delta_{T,c} time_{it} + \beta_{TT,c} time_{it}{}^2 + \beta_{Tco,c} time_{it} lncows_{it} + \beta_{Tca,c} time_{it} lncapital_{it} \\
& + \beta_{Tf,c} time_{it} lnfodder_{it} + \beta_{Tm,c} time_{it} lnmaterial_{it} + \beta_{To,c} time_{it} lnother_{it} \\
& + \beta_{Thl,c} time_{it} lnhiredlab_{it} + \beta_{Tfl,c} time_{it} lnfamilylab_{it} + \varepsilon_{it|c}
\end{aligned}
\qquad [1]
$$

with farm i in time period t and class c and ε denoting an independent and identically distributed (iid) stochastic term. As inputs for the Estonian technology model the following are considered: dairy cows (*cows*), capital costs (*capital*), fodder costs (*fodder*), material expenses (*material*), other costs (including veterinary expenses) (*other*), as well as family labour (*familylab*) and hired labour (*hiredlab*).

The Class identification component for the Estonian Class identification component is specified as follows:

$$P_{ic} = exp\begin{pmatrix}\theta_{0c} + \theta_{i01,c}i01 + \theta_{i02,c}i02 + \theta_{i03,c}i03 + \theta_{i04,c}i04 + \\ \theta_{i05,c}i05 + \theta_{i06,c}i06 + \theta_{i07,c}i07\end{pmatrix} / \left[\sum_i exp\begin{pmatrix}\theta_{0c} + \theta_{i01,c}i01 + \theta_{i02,c}i02 + \theta_{i03,c}i03 + \theta_{i04,c}i04 + \\ \theta_{i05,c}i05 + \theta_{i06,c}i06 + \theta_{i07,c}i07\end{pmatrix}\right] \quad [2]$$

where the q_{nit} identification related variables are the multi-dimensional indices for production structure (i01), farm environmental sustainability (i02), innovation (i03), production intensity (i04), production diversity (i05), individual/human capital characteristics (i06), and farm location (i07) for farm i in time period t, which are indicated in the tables of Annex D [TAD/CA/APM/WP(2020)2/ANN/FINAL].

2.2.3. Data and variables in the estimated model

Table 2.2 presents the main characteristics of the samples used in this study, while a series of tables in Annex D [TAD/CA/APM/WP(2020)2/ANN/FINAL] contains the descriptive statistical measures by country and farm type. The discussion of country case results in document [TAD/CA/APM/WP(2020)2/PART2/FINAL] contains a brief description of the farm data samples analysed in this study, and a definition of main output and input variables for each country case. It also presents the sample characteristics per estimated farm class.

The definition of farm types follows the EU FADN standard definitions.[2] If not received in a deflated form monetary data has been adequately deflated using price based deflators as used by national statistical agencies and EU Statistics.

Table 2.2. Overview of data used in the report

	Farm type	Period	Number of observations	Number of farms	Average number of years a farm appears in the panel	Source
Australia	Crop farms	1989-2018	8 921	3 687	4.7	ABARES, Canberra
	Dairy farms	1989-2018	9 161	2 367	3.9	
	Beef farms	1989-2018	9 092	2 723	3.4	
	Sheep meat farms	1989-2018	4 011	1 621	2.5	
	Wool farms	1989-2018	5 186	1 989	2.6	
	Mixed sheep-beef farms	1989-2018	4 787	1 869	2.8	
	Mixed crop and livestock farms	1989-2018	9 715	3 641	2.7	
Chile	Small-scale fruit farms	2015	448	448	1	Office of Agricultural Studies and Policies, Ministry of Agriculture of Chile (ODEPA)
Czech Republic	Dairy farms	2005-2015	1 011	156	6.5	Institute of Agricultural Economics and Information
Denmark	Dairy farms	2010-2016	17 121	2 871	5.9	Food and Resource Economics Institute at the University of Copenhagen
	Pig farms I	2006-2016	4 934	750	5.1	
	Pig farms II	2006-2016	9 524	1 369	6.9	
Estonia	Dairy farms	2000-2015	2 935	1 056	6.1	Ministry of Rural Affairs
France	Crop farms	1989-2016	50 786	7 602	6.7	Ministry of Agriculture and

[2] See, for example, http://ec.europa.eu/agriculture/rica and document 2003/369 (EC).

	Farm type	Period	Number of observations	Number of farms	Average number of years a farm appears in the panel	Source
	Dairy farms	1990-2013	28 711	5 628	5.1	Food
Hungary	Crop farms	2001-2014	14 128	2 937	5.5	Ministry of Agriculture and Research Institute of Agricultural Economics
Ireland	Crop farms	2010-2018	749	144	5.2	Teagasc
	Dairy farms	2010-2018	2 792	457	6.1	
	Cattle rearing farms	2010-2018	1 489	382	3.9	
	"Cattle other" farms	2010-2018	1 977	494	4	
	Sheep farms	2010-2018	1 147	247	4.6	
Italy	Crop farms	2008-2015	20 847	7 239	2.9	CREA at the Ministry of Agriculture
Korea	Rice farms	2003-2015	16 565	1 800	11	Korean Rural Economic Institute; Statistics Korea
Norway	Crop farms	2005-2016	1 613	285	5.7	Norwegian Institute of Bioeconomy Research (NIBIO)
	Dairy farms	2005-2016	5 549	948	5.8	
	Livestock farms	2005-2016	1 655	293	5.6	
Sweden	Crop farms	1997-2017	7 729	2 500	3.7	Jordbruksverket
	Dairy farms	1997-2017	3 940	1 000	3.1	Stockholm
United Kingdom	Crop farms	1995-2017	14 196	2 384	6	DEFRA, London
	Dairy farms	1995-2017	11 334	2 055	5.5	
	Pig farms	1995-2017	1 723	360	4.8	
	Poultry farms	1995-2017	4 415	1 260	3.5	
	Mixed crop-livestock farms	1995-2017	4 061	1 252	3.2	

3. Comparison of findings across case studies

3.1. The distribution of farms among estimated technology classes

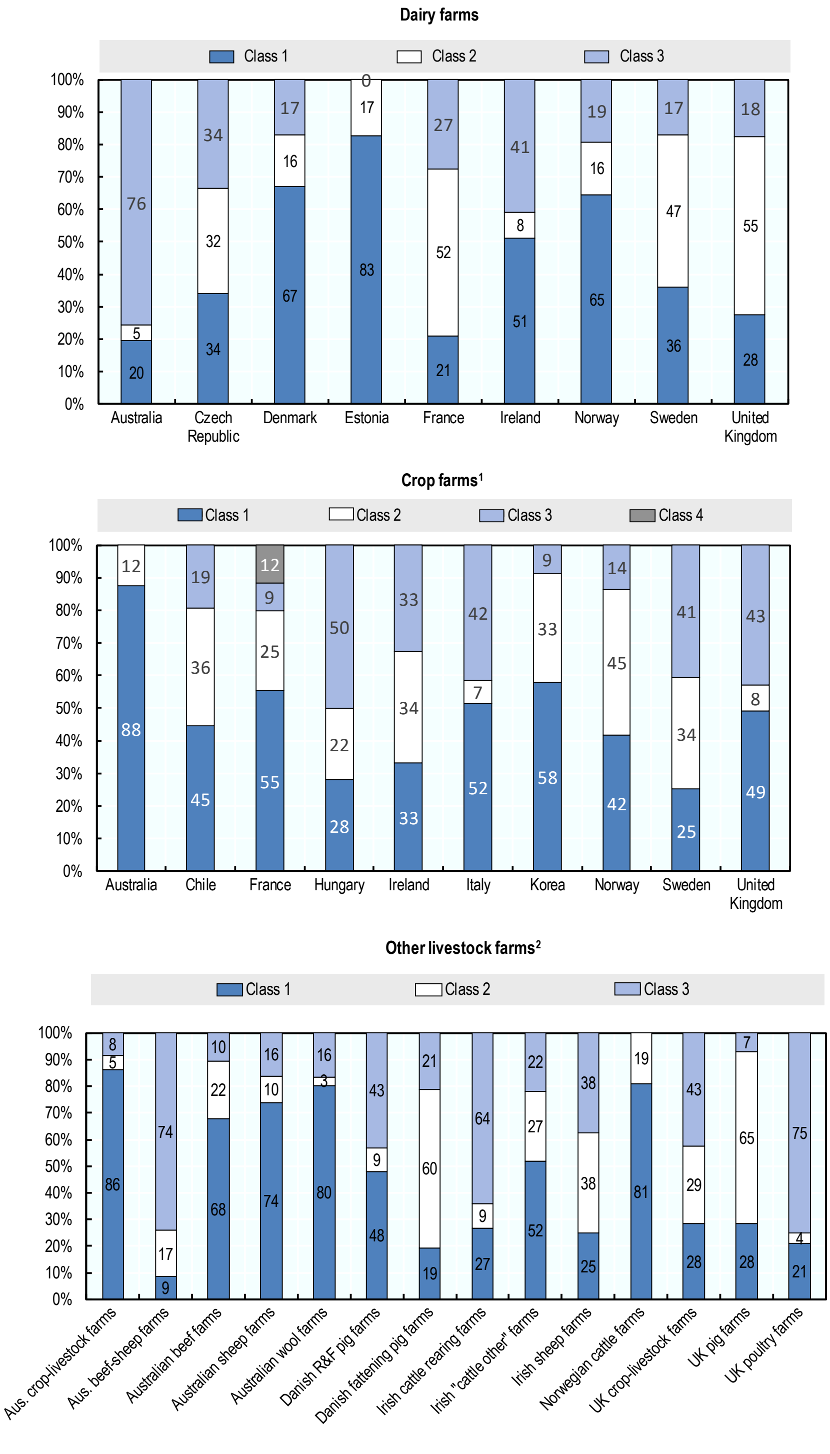
The analysis covers 33 farm case studies including thirteen countries and sixteen farm types, including dairy farms in nine countries, crop farms in seven countries and various crop, livestock and mixed farms (Table 1.1).

Most case study estimations result in the identification of three distinct technology classes. However, the estimation for crop farms in Australia, dairy farms in Estonia, cattle farms in Norway identifies two classes, and that for crop farms in France identifies four classes (Figure 3.1). In total, this results in 97 technology classes across all countries and farm types.

The **distribution of farms across technology classes** is uneven in most cases (Figure 3.1). In two-thirds of the 33 case studies, a majority of farms (over 50%) fall in one class. Among them, two dairy farm classes (Australia and Estonia), one crop farm class (Australia), and six livestock farm classes (four Australian farm types, Norwegian cattle farms and UK poultry farms) group over 75% of farms in their sample. These have usually high productivity, the exception being for dairy farms in Estonia, where a small share of farms achieves productivity levels more than four times higher than the average of all sample farms (Tables A C.1, A C.2 and A C.3; Figure 3.5). In another two dairy farm case studies (Denmark and Norway) and two livestock farms (Australian beef farms and UK pig farms), a farm class groups over two-thirds of all sample farms.

Figure 3.1. Distribution of farms across classes, by farm type and country

Percentage share of farms in each class in all sample farms



Notes: R&F: Rearing and Fattening. 1. Small-scale fruit farms in Chile, rice farms in Korea, cereal farms in the United Kingdom. 2. Other livestock farm cases include all cases of farms that are not specialised in dairy or crop production, i.e. mixed crop and livestock farms, cattle-beef farms, sheep farms, beef and sheep farms, wool farms, pig farms and poultry farms.
Source: Tables A C.1, A C.2 and A C.3.

Among the case studies with a very even distribution across technology classes, nine have a class with less than 10% of all sample farms (Figure 3.1). These are dairy farms in Australia and in Ireland, crop farms in Italy and the United Kingdom, beef-sheep farms and wool farms in Australia, rearing and fattening pig farms in Denmark, Irish cattle rearing farms and UK pig farms. In most cases, they are the classes with the lowest productivity (Tables A C.1, A C.2, A C.3).

Relatively even distributions are found in five cases: dairy farms in the Czech Republic, crop farms in Ireland, and to a lesser extent crop farms in Sweden, sheep farms in Ireland, and mixed crop-livestock farms in the United Kingdom (Figure 3.1).

Overall, crop farms studied tend to be more equally distributed across classes than other farm types, except in Australia. The concentration of dairy farms in a class varies by country, with highest levels found in Australia and Estonia. Other livestock farms display the highest number of unequal distribution, partly linked to the higher number of Australian farm types, but also the high concentration of some pig and poultry farms, illustrated in this study for Denmark and the United Kingdom. For Norwegian cattle farms, two unequal classes are identified, but they use technologies achieving very close productivity levels (Table 3.3).

3.2. Main productivity characteristics of estimated technology classes

Most case study estimations result in technology classes, with different productivity and technical change performance, which are shown in Table A C.1 for dairy farms, Table A C.2 for crop farms and Table A C.3 for all other livestock farm types in the case studies.

Productivity gaps – defined as the productivity level in a class as a percentage of the level in the most productive class – can be very large across classes (Figure 3.2). In many cases, the productivity ratio between the least and the most productive classes is around or over 50%.

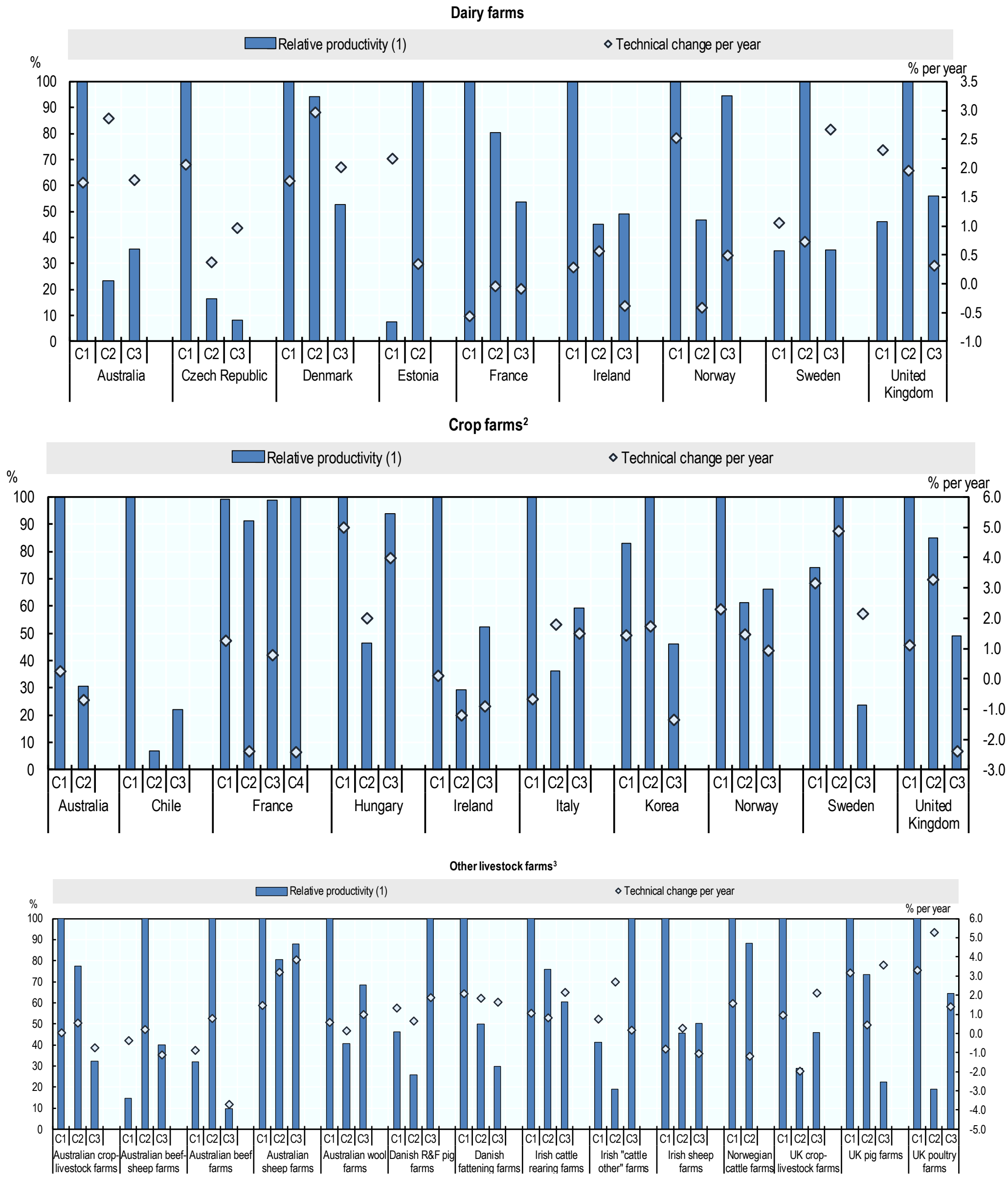
In ten case studies, the average productivity level in the least productive class is below 25% of the level in the most productive class, including three cases where the ratio is below 10%. The latter are dairy farms in the Czech Republic and in Estonia, and small-scale fruit farms in Chile. The other seven case studies, with productivity ratios between 10% and 25%, are: dairy farms in Australia, crop farms in Sweden, beef and sheep farms and beef farms in Australia, “cattle other” farms in Ireland, and pig farms and poultry farms in the United Kingdom. For the Australian and UK farm types, the least productive class accounts for less than 10% of all sample farms (Table A C.1, Table A C.2 and Table A C.3).

Conversely in a few case studies, estimations identify farm classes with relatively close productivity levels (less than 12% difference). This is the case for the three sheep farm classes in Australia, all four crop farm classes in France, and the two cattle farm classes in Norway. In several other cases, two classes have very close, higher productivity levels while the productivity in the third one is lower (e.g. dairy farms in Denmark, France and Norway; and crop farms in Hungary, Korea (rice) and the United Kingdom. There are also cases where the two less productive classes have very close productivity levels, such as dairy farms in Ireland and the United Kingdom; crop farms in Norway; and cattle rearing farms and sheep farms in Ireland. As discussed below, they can however have very distinct environmental sustainability performance.

Technical change is generally positive, reaching close to 3% per year for some dairy farm classes (e.g. in Denmark), close to 5% for crop farm classes (in Hungary and Sweden) and over 5% for a UK poultry farm class (Figure 3.2). The annual growth rate of technical change is particularly high in Hungarian and Swedish crop farms, and in class 2 crop farms in the United Kingdom. In addition, the rate of technical change is above 2.5% per year in some classes of dairy farms in Australia, Denmark and Norway, in classes of crop farms in Norway, and in classes of sheep farms in Australia, and pig and poultry farms in the United Kingdom.

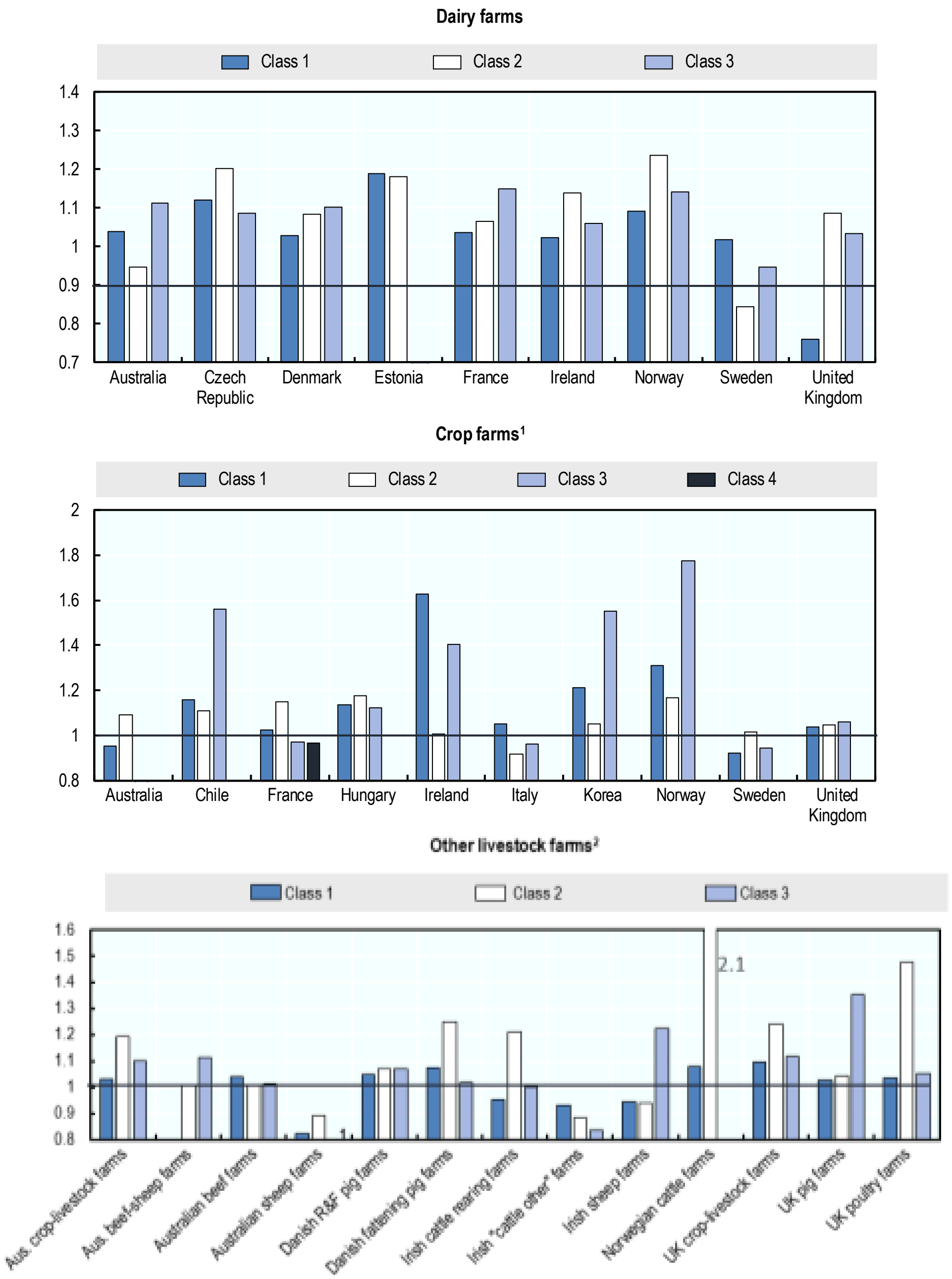
At the opposite range of the spectrum, there are also farm classes with declining technical change, mainly among crop and livestock farms. In most cases, these farms are also among the less productive classes, but this is not the case for crop farms in France and Italy, cattle farms in Norway, and Class 1 sheep in Ireland.

Figure 3.2. Relative productivity and technical change across case studies, by farm type, country and technology classes



Note: R&F: Rearing and Fattening. 1. Productivity level in the class as a percentage of productivity level in the most productive class. 2. Small fruit farms in Chile, rice farms in Korea, cereal farms in the United Kingdom. 3. Other livestock farm cases include all cases of farms that are not specialised in dairy or crop production, i.e. mixed crop and livestock farms, cattle-beef farms, sheep farms, beef and sheep farms, wool farms, pig farms and poultry farms.
Source: Tables A C.1, A C.2 and A C.3.

Figure 3.3. Estimated returns to scale across case studies, by farm type, country and technology classes



Note: R&F: Rearing and Fattening. 1. Small fruit farms in Chile, rice farms in Korea, cereal farms in the United Kingdom. 2. Other livestock farm cases include all cases of farms that are not specialised in dairy or crop production, i.e. mixed crop and livestock farms, cattle-beef farms, sheep farms, beef and sheep farms, wool farms, pig farms and poultry farms.
Source: Annex D tables [TAD/CA/APM/WP(2020)2/ANN/FINAL].

According to production function estimates, a large majority of farm classes exhibits increasing **returns to scale**, suggesting that an increase in herd size or area would result in additional revenue for the farms. This would be the case for most classes of dairy farms (22 of the 26 classes), and crop farms (22 of the 30 classes of crop farms). Of 41 other livestock farm classes, 25 also exhibit increasing returns to scale. Farm classes with decreasing returns to scales are mainly found for ruminant farms in Australia and Ireland, but also for four classes of dairy farms in Australia, Sweden and the United Kingdom, and for seven classes of crops farms in Australia, France, Italy and Sweden (Figure 3.3 above). Understanding the determinants of decreasing returns to scale would require further investigation. Farms in these classes should remove those factors that are limiting their productivity.

3.3. Divergence or convergence in productivity performance across classes

Within a case study, the comparison of productivity levels and technical change in each class shed light on whether productivity will diverge or converge across classes in the future and how fast convergence will be achieved given current technologies, *ceteris paribus*.

In cases where the most productive farms continue to have a higher estimated rate of technical change than their counterparts, the divergence in productivity levels across classes is growing (Figure 3.2). This diverging trend is found mainly among **crop farms**, although in the United Kingdom, technical change increases significantly faster in the medium productive class than in the most productive class of crop farms.

Cases of convergence, where the less productive classes show a higher rate of technical changes, suggesting they are catching up with the most productive class are most commonly found among **dairy farms**. Exceptions are in the Czech Republic and Norway, where differences between most productive and other classes are estimated to increase, and in Ireland and the United Kingdom, where the least productive class has a lower rate of technical change than other classes, while medium productive farms are expected to catch up. Productivity convergence across classes also occurs for crop farms in Italy, between medium and most productive crop farms in the United Kingdom, and between some crop farms in France, although in this latter case, productivity levels are very close.

The situation is very diverse among the 14 **other livestock farm** cases. Convergence is expected between all classes of Australian sheep farms, and Irish cattle other farms. Medium productive classes also catch up with most productive classes for Australian crop and livestock farms and UK crop and livestock farms, while least productive classes do so for Irish cattle fattening farms, Irish sheep farms, and UK pig farms and poultry farms. Divergence is expected for Australian bee-sheep farms and beef farms. The small difference in productivity levels between the two classes of Norwegian cattle farms is also expected to increase. Finally, productivity differences across classes is expected to remain stable for Australian wool farms, and the two types of Danish pig farms, as the three classes in each case have relatively close rates of technical change.

3.4. Potential productivity gains from the widespread adoption of the most performing technology

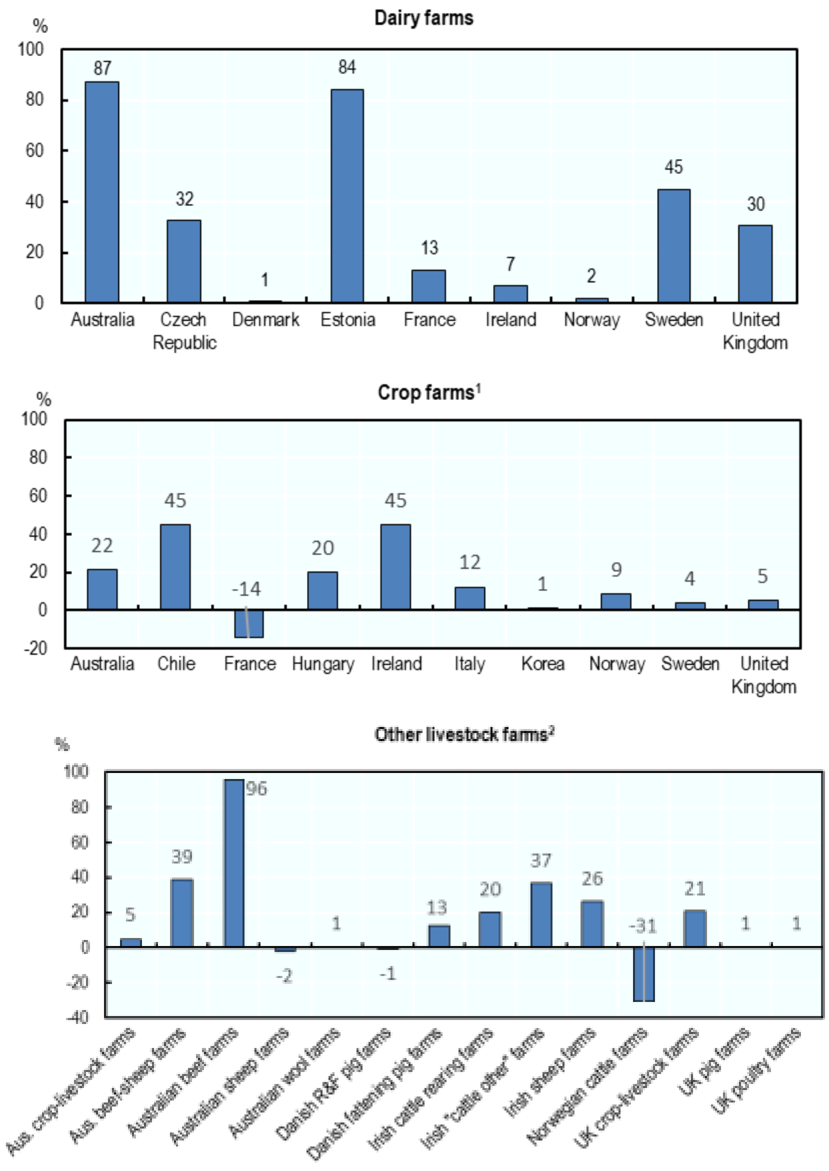
This section discusses the potential productivity changes estimated for farm specialist sectors if farms in the less productive classes could adopt the technology used in the most productive class. When interpreting the results, it should be kept in mind, however, that different productivity performance classes in countries often reflect natural resource and other constraints. For example, poorer performing dairy farms are often found in areas with natural handicaps, such as altitude, and poor soils or climate.

In most cases, the hypothetical adoption by farms in the less productive classes of the technology used in the most productive class would result in significant productivity gains in these classes and overall (Figure 3.4; Tables A C.5, A C.6, A C.7). Productivity gains are particularly large in cases with high productivity differences across classes, but the overall gain also depends on the distribution of farms across classes. Highest gains – over 80% – are found for dairy farms in

Australia and in Estonia, and beef farms in Australia. Lowest gains are in cases, where classes have similar technologies, or the least productive class accounts for a very small share of all farms (e.g. Korean rice farms, UK pig and poultry farms).

Figure 3.4. Overall productivity gains if most performing technology adopted, by farm type and country

% change in average productivity for all sample farms if all farm classes adopt the most performing technology



Note: R&F: Rearing and Fattening. 1. Small fruit farms in Chile, rice farms in Korea, cereal farms in the United Kingdom.
2. Other livestock farm cases include all cases of farms that are not specialised in dairy or crop production, i.e. mixed crop and livestock farms, cattle-beef farms, sheep farms, beef and sheep farms, wool farms, pig farms and poultry farms.
Source: Tables A C.4, A C.5 and A C.6.

The gains from adoption of the technology used in the most productive class by other classes also depend whether that technology is also the most productive for these other classes. In five cases, this adoption results in a decrease in productivity in these classes, which affects negatively the average productivity of all sample farms (Figure 3.3). These productivity losses for some classes might indicate that those farms have already adopted a productive technology given their locational/environmental constraints, which cannot be changed or optimised by the farmer (unless the farm would be relocated, which is not an option).

3.5. Main findings on drivers of performance across countries and farm types

3.5.1. Interpretation of multi-dimensional indices

For each case study, up to nine multi-dimensional indices are constructed based on variables available in the sample. The relative weights for the variables in the overall index estimation vary by farm type and country, as they are estimated within the Principal Component Analysis (PCA).

The multi-dimensional indices and their components are used in the analysis to identify the farm characteristics driving productivity performance. Table 2.1 provides a list of the variables potentially used in the estimations, while document [TAD/CA/APM/WP(2020)2/PART2/FINAL] contains tables (second table in each case study) listing the variables actually included in the indices estimated for each case study. These tables also report for each variable the deviation of the class average from the sample average. Similarly, document [TAD/CA/APM/WP(2020)2/PART2/FINAL] contains graphs and annex tables comparing the deviation of the multi-dimensional indices for each class from the sample average. Thus, within each case study, the comparison of productivity, variables and estimated indices allows the characterisation of each farm class relative to the sample average (sub-section 3.4.2). It also sheds light on the potential linkages between performance and other characteristics, and across characteristics (sub-section 3.4.3). Finally, it helps identify the characteristics of the most productive farm class (sub-section 3.4.4).

Interpretation needs to consider the composition of the indices, which reflects data availability and may differ by country. However, the core components are the same for each index. This composition of the multiple indices can be summarised as follow:

1. The **farm structure index** reflects the farm physical size in terms of number of hectares or animals, and the reliance on family labour. Classes with a negative value for the farm structure index include larger than average farms with lower reliance on family labour (i.e. more hired labour than the average of all farms). Conversely, a higher than average (positive) index is found for smaller-scale farms that are relying on family labour to a greater extent than the average of all farms.
2. The **environmental sustainability index** is a local measure which reflects the low intensity in chemical, fuel use and stocking density, and the use of environmentally sustainable practices, as measured by the probability to have organic production and the value of payments from voluntary participation in agri-environmental schemes, which is linked to the implementation of more environmentally sustainable practices. When interpreting the index, it should also be kept in mind that it may not reflect all the dimensions of environmental sustainability such as the impact on the climate. In addition, the pressure of farm practices on the environment depends on the state of natural resources at the local level. For example, low stocking density can be environmentally unsustainable in fragile areas.
3. The **innovation-cooperation-commercialisation index** reflects investments, expected to purchase new technologies, investment in land, new activities (agritourism, biofuel, contract farming) and sometimes the use of practices requiring specific technology.
4. The **technology index** groups various indicators of capital, labour and material intensity per hectare, per cow, or per worker as relevant.

5. The **diversity index** reflects the diversity of production using the Herfindahl index, which measures the degree of specialisation based on output shares, and in some countries the presence of other (e.g. forestry) activities on the farm. A higher index is found for less diversified farms.
6. The **individual-human capital index** reflects the gender, age, education and experience of the farm manager.
7. The **location index** indicates whether the farm is located in a favourable or more constraining environment, e.g. in terms of altitude, distance from urban centres, natural handicaps or specific environmental constraints (e.g. Natura 2000 in EU Member States).
8. The **household index** reflects the importance of off-farm income and the relative participation of women in the labour force, as well as other household characteristics if relevant.
9. The **financial index** reflects the financial health of the farm operation, including the size of assets, low debt level and the value of subsidies.

3.5.2. Main characteristics of farm classes based on estimated indices

Tables 3.1 to 3.3 provide a snapshot of the main characteristics of the 97 classes identified in the analysis, grouped by farm type. This helps to identify the farm classes likely to achieve the most desirable compromise in a given country and for a given farm type, as well as those with poor performance overall. It also helps understand some of the conditions that lead to this poor performance, how common they are, and whether they can be changed, for example using different technologies and practices. Document [TAD/CA/APM/WP(2020)2/PART2/FINAL] contains a more detailed discussion of the findings for the different classes in each study case, by country and farm type.

The discussion of findings on the characteristics of farm classes points to areas for improvement. For example, in some classes, farm performance could benefit from further economies of scales, or from the adoption of the best technology. These farms would take advantage of policies that facilitate adjustment and investment. In other classes, lower performance is explained by less favourable natural conditions, which cannot be changed. There are also cases where differences in investment and related performance between farm classes are likely to be related to individual characteristics of the farm household, such as the age of the manager, and the part-time nature of the agricultural activity.

Table 3.1. Dairy farms: Main characteristics of farm classes

	Class 1	Class 2	Class 3
Australia	Most productive and least environmentally sustainable farms, accounting for about 20% of all farms. They are much larger than average in terms of herd size, more specialised and more likely to be partnerships, and to rely on hired labour. They use the most intensive farming practices (stocking density and chemical per ha). They show the highest scores on innovation and a lower than average capital per labour intensity, based on high levels of total assets. Their managers are older and more educated than average, and more likely to be male. They have a lower debt ratio, and receive more subsidies than the average farm.	Least productive and most environmentally sustainable farms, accounting for less than 5% of all farms, and using the most extensive practices. They are less innovative, smaller and more reliant on family labour. Their production is more diversified, and less intensive than average. They receive less subsidies than average and have the highest share of off-farm income.	This class groups three-quarters of all farms, with intermediary productivity and environmental sustainability scores that are closer to Class 2, than Class 1 farms. They are smaller and more specialised, less innovative, and use more extensive practices than average. They also receive less subsidies than the average of all farms.

	Class 1	Class 2	Class 3
Czech Republic	Most productive and relatively environmentally sustainable farms account for a third of all farms. They are larger operations than average, and more reliant on hired labour. They are the most innovative, with higher investment in new technologies and practices, They use more capital per cow than average, based on high levels of assets.	Another third of all farms are the most environmentally sustainable that achieve relatively low productivity levels. They are more diverse, less innovative and less intensive. They invest less than average and their capital intensity is the lowest. They are more likely to be organic and receive higher agri-environmental payments.	Least productive and least environmentally sustainable farms account for the last third. They are smaller operations, more reliant on family labour, and more specialised than average. They invest far less in new technologies, and are more capital intensive than average. They are less likely to be located in less favoured or high altitude areas, and to participate in agri-environmental programmes.
Denmark	Two-thirds of all farms are in the most productive, least environmentally sustainable class. They are larger than average and more reliant on hired labour and contract farming. They are less-capital intensive than average, but score above average in terms of share of renting land and being engaged in contracting. Their managers are younger than average.	Most environmentally sustainable farms with close to highest productivity. With more land but less animals, they have the lowest stocking density, and are more specialised. They are managed by younger farmers that are more likely to invest in new technologies. They hold largest assets, higher debts and receive the highest amount of subsidy.	Least productive, with a slightly higher environmental sustainability score than average. They are smaller farms, more reliant on family labour, and managed by older farmers. They are more specialised, less innovative and intensive, but have lower debt ratios than average.
Estonia	Least productive, most environmentally sustainable farms accounting for 83% of all farms. They are smaller, more diversified operations, with a high share of family labour. Their managers are a bit older than average, use more extensive practices, and invest less than average. They are slightly more likely to be in areas with natural handicaps.	Most productive, least environmentally sustainable farms, with much higher (10 times) productivity levels than the others, but much lower technical change. They are much larger operations with younger than average managers, using hired labour. They have high investment in new technologies and capital intensity, and use more intensive farm practices.	
France	Most productive farms with slightly below average environmental sustainability account for over a quarter of all farms. They are more specialised, larger operations than average. They are endowed with higher assets, and are more likely to be partnerships and to be managed by older farmers. Investment in innovative technologies and activities is above average. They are more likely to use more extensive practices, including organic production.	Over half of all farms are in the least environmentally sustainable category and achieve productivity levels close to the highest. They are more diversified than others, use more intensive practices and are more likely to be in plains. They have scores close to the average of all farms for most other indices.	Most environmentally sustainable, least productive farms that are smaller than average in terms of herd size, and more specialised. They use more extensive technologies and farm practices and have lower capital intensity. They are more likely to be located in mountainous areas and have lower debt ratios than average.
Ireland[1]	Over half of farms are in the most productive, least environmentally sustainable category, and achieve small but positive technical change. They are much larger than average in terms of herd size and have more diversified operations. They invest much more in new technologies and activities than average and are more capital intensive, based on larger assets endowment than average. Their managers are younger and more likely to be women.	Least productive farms, with negative technical change and below average environmental sustainability account for less than 8% of all farms. They are have less animals than average, but are more diversified. They have lower than average levels of investment and capital intensity. Their managers are more likely to be older and male. They are more likely to be in less favoured areas, have lower assets and receive lower levels of subsidies.	Most environmentally sustainable farms, with close to lowest productivity and negative technical change account for about 40% of all farms. They are smaller operations, relying mainly on family labour, and their managers are older than average. They have lower than average levels of investment. They are more likely to be in less favoured areas, and have lower assets

	Class 1	Class 2	Class 3
Norway	Close to two-thirds of farms are in the most productive, least environmentally sustainable category. Of about average herd size, but with less land, they are more specialised operations, more likely to be partnerships. They are less capital intensive than average and have intermediary scores in terms of investment in new technologies. They are more likely to adopt organic practices, and they receive higher agri-environmental payments, but use more fuel per hectare. They rely more on off-farm income than average.	Least productive farms with an above average environmental sustainability account for 16% of all farms. They have a much smaller herd size than average and are managed by younger farmers, with higher reliance on family labour. They have the highest stocking density and receive lower agri-environmental payments. They have lower capital intensity than average, operate with a lower than average asset endowment and are less likely located in a favourable area.	Most environmentally sustainable farms, accounting for close to 20% of all farms, achieve productivity levels close to the highest in Class 1. They are much smaller than average and more diverse. They are more likely to be in mountainous areas and to use more extensive production practices. They receive lower levels of subsidies and have lower debt ratios than average.
Sweden	Least productive, most environmentally sustainable farms account for 36% of all farms. They are smaller, more specialised operations, with lower investments in new technologies and lower capital intensity. They are more likely managed by older men with lower education levels. They receive less subsidies than average and are more reliant on off-farm income than average.	More productive, least environmentally sustainable farms account for close to half of all farms. They are larger farms, with larger assets, which use more intensive farm practices. They invest in new technologies and are capital intensive. They are relatively diversified and receive higher levels of subsidies. They are more likely to be managed by women, with higher education levels than average.	The remaining 17% of farms are hardly more productive than the lowest performers, and their environmental sustainability score is slightly below average. They are smaller, more diversified operations, with lower investment than average. They are more likely to be in less-favoured areas and to have a female manager, with higher education levels than average.
United Kingdom	Most environmentally sustainable, least productive farms account for over a quarter of all farms. They are smaller, more specialised farms, which are more reliant on family labour. They are more likely to adopt agri-environmental practices and have land in less favoured areas. They are less capital intensive than average, and invest less in new technologies and practices. Their managers are older and less educated than average, and they have higher off-farm income.	Most productive farms achieving average environmental sustainability scores account for 55% of all farms. They are larger farms (herd size) that use hired labour, invest in new technologies and activities and use capital more intensively than the average farm. They are more likely to be in rural and hilly areas. Their managers are more educated than average.	Least sustainable farms account for close to 20% of all farms. They achieve productivity levels that are just above the average of the least productive performers in Class 1, with which they share similar characteristics, except that they are more diversified and have younger managers with lower education. They are more likely to be close to urban centres.

Note:
1. It is important to note that this analysis is based on the levels of total factor productivity and environmental pressure. Previous work by Buckley et al. (2019) for the same time period, using the same data, has shown that environmental emissions intensity (environmental footprint per unit of product produced) is lower on the better performing farms. Furthermore, based on the positive relationship between economic profitability and emissions efficiency, with the highest levels of emissions efficiency tending to be found on the most profitable farms, Buckley (*op. cit*) suggests that improvement in economic sustainability can be achieved side by side with improvements in emissions efficiency.
Source: [TAD/CA/APM/WP(2020)2/PART2/FINAL].

Table 3.2. Crop farms: Main characteristics of farm classes

	Class 1	Class 2	Class 3	Class 4
Australia	The most productive and least environmentally sustainable class groups close to 90% of all farms. They are larger operations that are more likely to be partnerships and be engaged in contracting. They have less diversified production, more intensive farming practices, higher investment in new technologies than average and farm more intensively. Their managers are younger than average and more educated.	The few most environmentally sustainable and least productive farms are smaller, more diversified operations than average with a higher share of family labour and more extensive farming practices (fuel and chemical use per ha). They are managed by older farmers and are more reliant on off-farm income. They have lower investment in new technologies and practices, and lower debt ratios, but are more capital intensive than average.		
Chile[1]	Most productive farms are also the most environmentally sustainable, accounting for about 45% of all farms. They operate larger areas and use more hired labour than average. They have higher capital intensity than average, adopt more innovative technologies, and spend more on advisory services. They are more likely to farm organically and to be closer to urban centres. They receive higher subsidies than average. Managers are slightly younger and better educated than average.	Least productive and environmentally sustainable farms account for 36% of all farms. They are smaller than average, and are managed by younger, but more experienced and educated farmers, more likely to be ethnic women. They have lower scores on innovation and are more likely to be located far from an urban centre.	The remaining 19% farms achieve lower than average productivity and environmental sustainability. They are larger farms, with more extensive, less innovative practices and lower capital intensity. They are more likely managed by older farmers, with lower education and experience in farming. They receive less subsidies than average.	
France[1]	55% of all farms achieve close to highest productivity, and above average environmental sustainability. They are larger operations (in ha) and are more likely to be partnerships. They invest more in new technologies and are more capital intensive than average. They receive the highest subsidies.	Least productive farms account for a quarter of farms and achieve lower than average environmental sustainability. They are smaller, more intensive and specialised operations, with lower investment and capital intensity than average. They are more likely to be located in remote areas, and to have off-farm income.	About 8% of all farms have close to highest productivity, but are the least environmentally sustainable. They are the smallest operations, most diversified and reliant on family labour. They are managed by younger farmers and have high investment rates, and high capital per ha.	Most productive and environmentally sustainable farms account for 12% of all farms. As in Class 1, they are larger operations and are more likely to be partnerships, but rely more on family labour. They are managed by older farmers, which invest less but are more likely to have biofuel production. They are also more likely to be in more rural areas.

	Class 1	Class 2	Class 3	Class 4
Hungary	Most productive, with the highest technical change rate, and least environmentally sustainable farms, accounting for 28% of all farms. They are smaller (ha), rather specialised operations, with a higher share of family labour. They use more input intensive practices and are managed by younger farmers than average. They are more likely to be located in nitrate vulnerable zones.	Least productive farms (22%), achieve average environmental sustainability. They are the smallest operations, with high labour intensity. They are more likely to be located in areas with natural handicaps and to be managed by older farmers.	Half of all farms are in the most environmentally sustainable category, and achieve close to highest productivity levels. They are the largest operations, with higher shares of hired labour. They are managed by younger farmers, who participate more than average in agri-environmental programmes	
Ireland	Most productive farms, with lower than average environmental sustainability account for a third of all farms. They are larger (ha) operations, with a higher share of family labour than average. They use variable inputs and capital more intensively than average. They invest much more than other farms in new technologies. They receive more subsidies per ha and have much higher assets than average. Their manager is more likely to be a woman, to have less agricultural training and to be younger than average.	Least productive farms are also the least environmentally sustainable and account for another third. They are smaller, more specialised operations, with lower investment in technologies. They are more likely to be engaged in contract farming and to cultivate energy crops. Their managers are older and have better agricultural training. They are more likely to be part-time and have a higher share of off-farm income.	The last third is made of most environmentally sustainable farms achieving productivity levels close to the Class 1 average. They are smaller, more diversified operations than average, and are more likely to be engaged in agri-environmental schemes. They have low capital intensity and are more likely to be in less-favoured areas. Overall, they receive less subsidies per ha than average.	
Italy	Over half of all farms are most productive farms achieving lower than average environmental sustainability. They are larger, more specialised operations that are more likely to be partnerships. Managed by younger and better educated farmers, they have high capital intensity and intensive practices.	Least environmentally sustainable farms, which are also the least productive account for 7% of all farms. They are smaller, more diversified operations with a higher share of family labour than average. Their manager is older than average and they are most likely located in less-favoured areas and at higher altitude	Most environmentally sustainable farms account for over 40% of all farms, and achieve medium productivity levels. They are of average size and reliant on family labour, with older than average managers. They are relatively more specialised and have low capital intensity. Their managers are significantly older than average.	
Korea[2]	Close to 60% of all rice farms achieve productivity levels 15% lower than the highest, with an environmental sustainability above the average. In terms of physical size (ha), they are close to the average, use more extensive farming practices but are more capital intensive. They are more likely to be managed by older women and to be located in les-favoured areas.	The most productive farms, which account for a third of all farms, are the least environmentally sustainable. They are the largest, and most intensive operations. They are less diversified than average, and invest more in new technologies. They are more likely to be managed by more educated, younger farmers. Off-farm income is important for them.	The most environmentally sustainable farms, which are also the least productive, account for a small share of all farms (9%). They are the smallest, and most extensive farm. They invest less than other rice farms and are less capital intensive.	

	Class 1	Class 2	Class 3	Class 4
Norway	Most productive farms, which account for 42% of all farms, are the least environmentally sustainable. They are smaller, less diversified operations, with more intensive practices and higher capital intensity per labour. They are managed by older farmers, more likely to be women. They generate below average off-farm income and receive below average subsidies.	Most environmentally sustainable farms are the least productive and account for 45% of all farms. They are larger operations, more likely to rely on hired labour. Managers farm more sustainably and are more likely to adopt organic practices. They invest relatively less than other farms and have low capital intensity. But they have higher assets, receive more subsidies and have higher off-farm income.	Close to 15% of farms have productivity levels slightly above the weakest category and below average environmental sustainability. They have less land and lower assets, but they are the most capital intensive and more likely to use contract farming. Managers are more likely to be younger than average and women. They receive below average subsidies.	
Sweden	Over a third of all farms achieves productivity levels slightly higher than least performers, and lowest environmental sustainability. They are of average size, more specialised and use more intensive farm practices than average. They are more capital intensive but invest less in new technologies and activities. They generate below average off-farm income and have higher debt ratios.	Most productive farms, accounting for 44% of all farms, are also the most environmentally sustainable as they use more extensive and environmentally-friendly practices. They are larger operations, more likely to be partnerships. The have more diversified productions, with higher investment in new technologies and activities. They have larger assets than average but higher debt ratios.	About 20% of farms are least productive and achieve average environmental sustainability, as measured by the intensity of farming practices. They are smaller and more diverse operations than average. They are more likely managed by women and to generate a higher share of off-farm income. They are less capital intensive than average, invest less in new technologies, and have lower debt ratios.	
United Kingdom[3]	Most productive farms account for about half of all farms and achieve below average environmental sustainability as they have more intensive farming practices than average. They are larger, more diversified operations, which invest in new technologies and activities. They are more capital intensive and achieve higher financial ratios. Their managers are more likely to be men, older than average and a with better education level.	The 8% least environmentally sustainable farms, with the most intensive farm practices, achieve close to highest productivity levels. They are smaller and more specialised operations than average. They are capital intensive and invest in new technologies. They are more reliant on off-farm income and their financial performance is lower than average.	Most environmentally sustainable farms using most extensive farm practices are the least productive. They account for 43% of all farms and are smaller and more specialised than average. They are more likely to be managed by women, with lower education levels. They are less capital intensive than average, and have lower investment in new technologies.	

Notes:
1. Small-scale fruit farms.
2. Rice farms.
3. Cereal farms.
Source: [TAD/CA/APM/WP(2020)2/PART2/FINAL].

Table 3.3. Other livestock farms: Main characteristics of farm classes

	Class 1	Class 2	Class 3
Australian crop-livestock farms	Over 85% of crop and livestock farms belong to the most productive, least environmentally sustainable category, as they use more intensive farming practices than average. There are more specialised farms, with an average area, but larger herds, and thus higher stocking density. They are more capital intensive than average and likely to be engaged in contract farming. They are managed by younger farmers, and have lower off-farm income.	About 5% of farms achieve medium productivity and above average environmental sustainability. They are larger, operations, more likely to be partnerships and to depend on family labour. They are more diversified and more extensive operations than average They invest more in new technologies, and are less likely to be engaged in contract farming. They receive more subsidies than average and have lower debt ratios.	Most environmentally sustainable farms, which are the least productive account for the remaining 8% of all farms. They are smaller than average operations with higher stocking density but lower use of chemicals per ha. They are the most specialised farms. They are more capital intensive per ha but invest less in new technologies than average. Managers are older and more likely to be men. They have the highest share of off-farm income.
Australian beef-sheep farms	Most environmentally sustainable farms account for less than 10% of all farms and are the least productive. They are the smallest operations in terms of herd size, with highest share of family labour. They use the most extensive farming practices but are capital intensive. They have a lower asset endowment and lower debt ratios than average. They are more likely to be located in a pastoral zone, and to be more dependent on off-farm income.	Most productive farms (17% of all farms) are the least environmentally sustainable. They are the largest operations, more likely to be organised as partnerships and to be located in a high-rainfall zone. Their manager is older than average and better educated. They have the highest levels of investment in new technologies and are more likely to use contract farming than other farms. They are endowed with larger assets and are slightly more indebted than average.	Close to three-quarters of farms have below average productivity, but higher environmental sustainability as they use more extensive farming practices. They are larger than average operations, with lower levels of investments. They invest less than the average farm in new technologies.
Australian beef farms	Over two-thirds of farms have average environmental sustainability, and below average productivity. They are larger than average operations in terms of area and herd size. They are close to the average for most indicators of technology and practices, but their manager is older and more educated than average and more likely to be a woman. Their asset endowment is below average.	Most productive farms account for 22% of all farms and are the least environmentally sustainable, as these farms have the most intensive farming practices of all. They are smaller, more diversified operations, with assets well above average. They invest slightly more in new technologies and activities than average, and have higher debt ratios than average. Their manager is younger and less educated.	Most environmentally sustainable farms, which account for 10% of all farms, are the least productive. They are the largest, most diverse operations. They are less capital intensive than average and are less likely to use contract farming. They generate a higher share of off-farm income, and lower debt ratios, but have smaller asset endowment.
Australian sheep meat farms	Close to three-quarters of all farms are most productive and also most environmentally sustainable. They are more diverse operations, with the largest herds, but only above average land area. As a result, they have the highest stocking density, but otherwise use less chemicals and fuel per ha. Their capital intensity and investment in new technologies is below average.	Least productive farms, accounting for 10% of all farms, have lower than average environmental sustainability, due to lower stocking density. They are smaller in terms of herd size and land, and most specialised operations, with high capital intensity. They are managed by older and more educated farmers, more likely to be women. They have the highest share of off-farm income, receive the highest amount of subsidies and have lower debt ratios.	Least environmentally sustainable farms (16%) have a productivity slightly higher the lowest one. They are the largest and most innovative farms and are more capital intensive than average. They are less diversified than average, their manager is younger, but better educated than average. They receive the lowest amount of subsidies and obtain the lowest share of off-farm income.

	Class 1	Class 2	Class 3
Australian wool farms	Over 80% of all farms are most productive and most environmentally sustainable, as they use more extensive farming practices. They are smaller and more diverse operations, with lower than average investment in new technologies and the lowest capital intensity. Given their large number, they are close to average scores, which they determine to a large extent.	This class groups the 3% least productive farms, with a below average environmental sustainability driven by their high stocking density. They are the largest, most diverse operations, with older and more educated than average managers, more likely to be women. They have the highest share of off-farm income, receive less subsidies and have lower debt ratios.	Least environmentally sustainable farms achieve medium productivity. They are larger than average, more specialised operations, with the most intensive farming practices. They have the highest levels of investment in new technologies and practices and the highest capital intensity. They are managed by younger farmer and their household is less dependent on off-farm income. They have the largest asset endowment, receive the highest subsidies and their debt/equity ratio is slightly below average.
Danish rearing and fattening pig farms	48% of all farms are medium productive and achieve average environmental sustainability. They are smaller, more diversified operations, relying more on family labour, and managed more likely by older farmers. They receive less subsidies than the average farm. They invest slightly less than average.	Most environmentally sustainable farms, which are the least productive, account for less than 10% of all farms. They are less diversified, smaller operations, with higher share of family labour and older managers that are less likely to have a successor. They receive higher environmental subsidies than average and are more likely to farm organically. They are the least innovative, invest significantly less than average and are less capital intensive.	Most productive farms, which account for 43% of all farms are the least environmentally sustainable. They are larger, more specialised farm operations, more likely to have hired labour and be organised as a partnership. They invest more in new technologies and activities and are more capital intensive. They are more likely to be managed by younger farmers, which have larger assets and receive more subsidies.
Danish fattening pig farms	Most productive farms are the least environmentally sustainable. They account for about 20% of all farms. They are larger, more specialised operations, more likely to be partnerships and managed by younger managers. They are more capital intensive and invest more in new technologies and activities. They have higher levels of off-farm income than average.	About 60% of all farms have medium productivity and average environmental sustainability. They are smaller than average operations, more likely to have a successor and to use contract work. They employ more labour per capital than their counterparts in Class 1. For other indices and variables, they have a medium score.	Most environmentally sustainable farms are the least productive and account for about 20% of all farms. They are the smallest, least diversified of all farms, with higher reliance on family labour and less likely to have a successor. They invest less than average and have lower capital intensity and lower debts.
Irish cattle rearing farms	Most productive farms are also the most environmentally sustainable due to extensive practices. Accounting for over a quarter of all farms, they are the largest operations in terms of herd size and have the most diversified production. They have a higher share of hired labour than average and are more likely to be managed by younger farmers. They have higher levels of investment in new technologies and activities and higher capital intensity than average. They receive more rural support but generate less off-farm income than average.	Least environmentally sustainable farms achieving medium productivity account for less than 10% of all farms. They are the largest operations in terms of herd size, with more intensive farming practices, including higher stocking density They also have lower capital intensity but higher investment in new technologies than average. They are less likely to be located in less favoured areas. They are likely to be managed by older men that have higher levels of off-farm income, and higher assets and they receive much more subsidies than average.	64% of all farms are least productive and achieve average environmental sustainability. They are smaller, more specialised operations, with lower investment in new technologies than average, and lower assets. They receive less subsidies than average and have close to average scores on most other variables.

	Class 1	Class 2	Class 3
Irish “cattle other” farms	Over half of farms are medium productive and achieve slightly above average environmental sustainability. They have slightly below average herd size, and have relatively lower investment and capital intensity than average. They are managed by farmers with lower agricultural training and are more likely to be in hilly and less favoured areas. They also generate higher than average off-farm income levels. They are close to the average of all farms for most other variables.	Most environmentally sustainable farms, which account for over a quarter of all farms, are the least productive. They are less diversified operations, with a higher share of family labour, much smaller herds and lower stocking density, and generally more extensive farming practices. They are less capital intensive and invest less in new technologies and activities, than average They have the lowest assets and receive the lowest subsidies.	Most productive and least environmentally sustainable farms, using most land intensive practices, account for 22% of all farms. They are larger, more diverse operations, with higher levels of investment in new technologies and activities, and higher than average capital intensity. They have higher assets, and receive more subsidies than average. They are managed by younger farmers with better agricultural training. They are less likely to be in less-favoured areas and they have lower off-farm income.
Irish sheep farms	Most productive farms (about a quarter of all farms) are also the least environmentally sustainable. They are the largest operations in terms of herd size and the most diversified. They have the highest investment in new technologies and activities than average and are the most capital intensive farms. They are managed by younger farmers, with a higher education in farming, and are the least likely to be located in less-favoured or hilly areas. They have higher asset levels, receive more subsidies and generate less off-farm income than average.	Least productive farms are more environmentally sustainable than average and account for 38% of all farms. They are the most likely to be located in less favoured areas and have the lowest levels of asset and subsidies, but receive more rural support. They are more likely to be managed by a man, to be part-time farms, and to generate high levels of off-farm income.	Most environmentally sustainable farms, which account for 27% of all farms, achieve productivity levels that are slightly higher than the lowest. They are smaller, more specialised operations, with a higher share of family labour. They are less capital intensive than average and have lower investment in new technologies and activities. They are the least capital and labour intensive of all farms. Their levels of assets and subsidies is close to that of farms in Class 2.
Norwegian cattle farms	Over 80% of all farms achieve productivity levels that are close to the highest (12% lower), but with worse environmental sustainability performance. They are smaller operations (ha) with smaller herd size. They are less diversified operations and more likely to be managed by older farmers or women. Their capital intensity is lower than average and they employ the highest rate of labour per capital animal.	The most productive farms are also the most environmentally sustainable and account for about 20% of all farms. They are larger operations with a higher share of hired labour. They are more diversified and capital intensive than average, and more likely to be managed by younger men. They have larger assets and receive more subsidies than average. They are also more likely to have income from forestry.	
UK crop-livestock farms	Most productive farms, which account for over a quarter of all farms, are the least environmentally sustainable, as they use more intensive farm practices. They are larger, more specialised operations, which are more likely to be partnerships. They invest more in new technologies and activities and are more capital intensive than average. They are more likely to be managed by men with higher than average education levels.	Least productive farms (about 40% of all farms), achieve slightly below average environmental sustainability. They are smaller than average operations, with a higher share of family labour. They are less capital intensive and invest less in new technologies. They are more likely to be in less-favoured areas, receive more subsidies and have a higher share of off-farm income than average.	Most environmentally sustainable farms using more extensive and environmentally sustainable farm practices, have medium productivity and account for about a third of all farms. They are the smallest, most diversified operations. They are more likely to be managed by women with higher than average education levels, and to be located in hilly, rural areas. They have lower debt ratios than average and receive less subsidies.

	Class 1	Class 2	Class 3
UK pig farms	Most productive farms account for 28% of all farms and score below average in terms of environmental sustainability. They are the largest, most diversified operations, and the most likely to be partnerships, with managers having better education. They have the highest capital intensity and investments in new technologies, building on large assets. They are more likely to be located in a less-favoured and a rural area. They receive the highest level of subsidies and have lower debt ratios.	Most environmentally sustainable farms account for close to two-thirds of all farms and achieve below average productivity. They are smaller and more specialised operations than average, with lower investment in new technologies and capital intensity. Their managers are more likely to be younger, women, and with lower education levels than average. They are below average in terms of asset endowment, subsidy received and equity/debt ratio.	7% of all farms are least environmentally sustainable and least productive. They are the smallest operations, least capital intensive operations, which invest the least in new technologies. Their manager is more likely to be older and male. They are more likely to be located in hilly, rural areas, but not less favoured areas. They have the lowest asset endowment and are the most reliant on off-farm income.
UK poultry farms	Most productive and least environmentally sustainable farms account for 21% of all farms. They are the largest, most specialised operations, which are the most likely to use hired labour and be organised as partnerships. They have more intensive farm practices than average, but receive highest amounts of agri-environmental payments. They have the highest level of investment in technologies and practices and are the most capital intensive, with highest asset endowment. They are most likely managed by men with better education. They are also likely to be located in hillier and more rural areas.	Most environmentally sustainable farms, which are also least productive, account for 4% of all farms. They are the smallest operations, with the highest share of family labour. They have the lowest level of investment in new technologies and use more capital and material per animal than average. Their manager is likely to be older, to be a woman and to have a lower education level. They are more likely to be in a less-favoured area and are the most reliant on off-farm income. They receive the highest amount of subsidies and have lower debt ratios.	Three-quarters of all farms achieve below average productivity, and above average environmental sustainability. They are smaller operations than average, and invest less in new technologies. They are close to the average of all farms for all other indices, including technology, household and financial, given their importance in defining the average of all farms.

Source: [TAD/CA/APM/WP(2020)2/PART2/FINAL].

3.5.3. Linkages between selected characteristics

For each case study, Tables 3.4 to 3.7 compare the estimated scores of most productive and most environmentally sustainable classes – calculated as the deviation from the sample average – for the multi-dimensional indices used to estimate the technology classes. This comparison, which uses the rules defined in the notes to Table 3.4, relates productivity performance and environmental sustainability performance with farm characteristics represented by other estimated indices. For some characteristics, common relationships emerge across case studies, but for other cases, the situation is more diverse. The correlations also vary by farm type.

The relationship between **productivity and environmental sustainability**, as measured by the estimated index, which mainly reflects the environmental pressure of farming practices per ha, is found to be mainly negative, in particular for dairy farms and pig and poultry farms, but less frequently so for ruminant farms (Tables 3.4, 3.6 and 3.7). For crop farms, there is no systematic trade-off between productivity and environmental sustainability. The relationship is clearly positive in three of the ten countries included in the study. Moreover, in a number of other cases, the environmental sustainability index of the most productive class is above the sample average, although not the highest (Table 3.5; Figure 3.4). For crop farms in Hungary, the most productive class is the least environmentally sustainable, but the productivity level of the most environmentally sustainable class is only 6% lower.

Examples of strong positive relationships – with both the most productive class being the most environmentally sustainable and the least productive the least environmentally sustainable - are found for small-scale fruit farms in Chile, and cattle farms in Norway, although in the latter case, the two classes achieve productivity levels that are not so different. The most productive class is also the most environmentally sustainable for crop farms in France and in Sweden, sheep farms and wool farms in Australia, and cattle rearing farms in Ireland.

There are also cases of a weaker trade-off between productivity and environmental sustainability among dairy and other breeding farms. For example, the environmental sustainability index for the most productive class of Czech dairy farms is above the sample average and the least productive class is also the least environmentally sustainable (Figure 3.5). For pig farms in the United Kingdom, the most productive farm class has an environmental sustainability index below average, but the least productive class is also the least environmentally sustainable and the most environmentally sustainable class achieves relatively high productivity levels (12% below the most productive class) (Figure 3.5).

Regarding **farm structure**, the relationship between productivity performance and the farm structure index is mostly negative, meaning that the most productive farms are larger than average and rely more on hired labour. Conversely, least productive farms are smaller operations with a higher share of family labour. The most environmentally sustainable dairy farms and non-ruminant farms are generally smaller and more reliant on family labour. However, for ruminant farms and crop farms, the relationship is positive in half the cases, meaning that most environmentally sustainable farms are also larger than average.

In almost all cases, **innovative farms**, which invest in new technologies and develop new activities, are likely to achieve higher productivity levels. In many cases, innovative dairy and livestock farms are also likely to achieve lower than average environmental sustainability, but in about half the cases, innovative crop farms are also the most environmentally sustainable.

Farms using capital intensive **technologies** are also found to achieve higher productivity in a large majority of cases, in particular for crop and dairy farms, but less frequently for other livestock farms. The environmental sustainability performance of farms with a higher technology index is often lower than average, in particular for crop farms. There are, however, several cases of dairy and livestock farms investing in new technologies and activities, which achieve higher than average environmental sustainability.

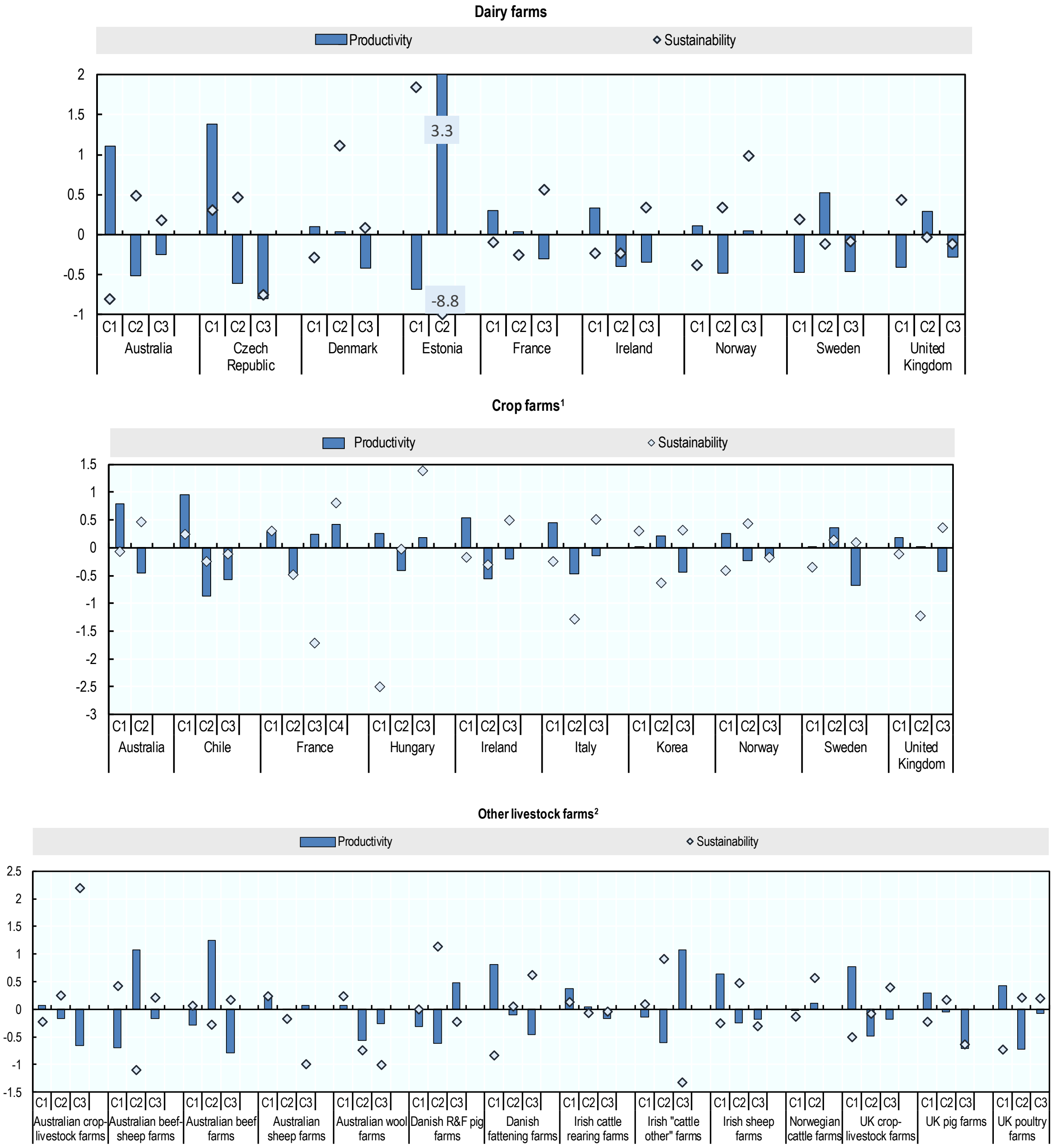
Production diversity is often associated with average or higher productivity for dairy and livestock farms. In contrast, more specialised crop farms are likely to have higher productivity, and in half the cases, they also likely to have higher than average environmental sustainability. Diversified dairy farms also tend to be more environmentally sustainable than average, as do a majority of diversified livestock farms, while the relationship between diversity and environmental sustainability varies across countries for crop farms.

More productive dairy and livestock farms tend to have healthier **financial** ratios, while the relationship is more diverse for crop farms. A large majority of more environmentally sustainable farms are likely to have weaker financial performance.

Indices for human capital, farm location and farm household control for individual farmer and farm related characteristics. The fact that these characteristics are controlled for in the PCA that identifies farm classes strengthens the robustness of estimates. Thus these control indices cannot be interpreted in terms of correlations or directions as the ones discussed above.

Figure 3.5. Relative productivity and environmental sustainability across case studies, by farm type, country and technology classes

Deviation from sample mean (ratio)



Notes: R&F: Rearing and Fattening. 1. Small fruit farms in Chile, rice farms in Korea, cereal farms in the United Kingdom.
2. Other livestock farm cases include all cases of farms that are not specialised in dairy or crop production, i.e. mixed crop and livestock farms, cattle-beef farms, sheep farms, beef and sheep farms, wool farms, pig farms and poultry farms.
Source: Figures and Tables in document [TAD/CA/APM/WP(2020)2/PART2/FINAL].

Table 3.4. Dairy farms: Trade-off and synergies between farm performance and farm characteristics

	Australia	Czech Republic	Denmark	Estonia[1]	France	Ireland	Norway	Sweden	United Kingdom	Share of positive
Relationship between productivity performance and the following characteristics[2]										
Farm structure	---	---	---	+++[1]	--	--	M+	--	---	Mostly negative
Environmental sustainability	---	+	--	---	---	--	--	---	M-	Mostly negative
Innovation-commercialisation	+++	+++	+++	+++	+++	+++	M-	++	++	Mostly positive
Technology	--	++	M-	+++	+++	M+	-/+	+++	++	Majority positive
Production diversity	M-	+	+	---	+++	M-	M-	+	M-	Mainly average or better
Financial health	+++		+	+++	++	+++	-/+	+++	++	Mostly positive
Relationship between environmental sustainability performance and the following characteristics[2]										
Farm structure[1]	+++	+/-	M-	---	++	+++	--	+++	++	Mostly positive
Innovation-commercialisation	----	-/+	M+	---	--	---	M-	-	-/+	Mainly negative
Technology	-/+	--	++	---	--	++	++	--	-/+	Mostly negative
Production diversity	+++	+++	++	+++	--	M+	M+	--	+++	Majority negative
Financial	M-		++		--	---	++	---	-/+	Diverse

Notes: 1. For Estonian dairy farms, the share of hired labour is used rather than the share of family labour in other cases.

2. The following signs and rules are used to assess relationships between performance and indices.

- +++ Indicates that the most productive (environmentally sustainable) class has the highest index, and the least productive (environmentally sustainable) class the lowest index.
- --- Indicates that the most productive (environmentally sustainable) class has the lowest index, and the least productive (environmentally sustainable) class the highest index.
- ++ Indicates that the most productive (environmentally sustainable) class has the highest index, but the least productive (environmentally sustainable) class does not have the lowest index.
- -- Indicates that the most productive (environmentally sustainable) class has the lowest index, but the least productive (environmentally sustainable) class does not have the highest index.
- + Indicates that the most productive (environmentally sustainable) class has a positive index, but not the highest.
- \- Indicates that the most productive (environmentally sustainable) class has a negative index, but not the highest.
- M+ Indicates that the most productive (environmentally sustainable) class has a positive index, but below 0.06 (i.e. close to the sample average).
- M- Indicates that the most productive (environmentally sustainable) class has a negative index, but above -0.06 (i.e. close to the sample average).
- +/- Indicates that both the most and the least productive (environmentally sustainable) classes have a positive index, but the index of the least productive class is higher.
- -/+ Indicates that both the most and the least productive (environmentally sustainable) classes have a negative index, but the index of the least productive class is lower.

Source: Figures and tables in document [TAD/CA/APM/WP(2020)2/PART2/FINAL].

Table 3.5. Crop farms: Trade-off and synergies between farm performance and farm characteristics

	Australia	Chile	France	Hungary[1]	Ireland	Italy	Korea	Norway	Sweden	United Kingdom	Comments
Relationship between productivity performance and the following characteristics[2]											
Farm structure	---	--	--	++	---	---	---	+	--	--	Mostly negative
Environmental sustainability	---	+++	++	--[1]	-/+	-/+	---	---	++	-	Mostly negative
Innovation-commercialisation	+++	+++	+++	--	+++	+++	+++	+	+++	+++	Mostly positive
Technology	+++	++	--	++	++	++	+++	+	-	M-	Mainly positive
Production diversity	---	M-	-/+	++	-	---	--	--	M+	+++	Mainly negative
Financial health	+++	0	-/+		+++	0	0	---	---	+++	Diverse
Relationship between environmental sustainability performance and the following characteristics[2]											
Farm structure[1]	+++	--	---	---	M+	+/-	+++	--	---	+/-	Mainly negative
Innovation-commercialisation	---	+++	++	+++	M-	-/+	---	--	+++	++	Diverse
Technology	---	++	---	--	--	--	---	--	-	-	Mostly negative
Production diversity	+++	M-	---	+	--	+/-	+++	M-	+/-	M+	Diverse
Financial	---		-		-/+			+++	---	--	Diverse

Notes:
1. In Hungary, the most productive class is the least environmentally sustainable, but most environmentally sustainable class achieves a 6% lower average productivity.
2. The signs and rules used to assess relationships between performance and indices are described in notes to Table 3.4.
Source: Figures and Tables in document [TAD/CA/APM/WP(2020)2/PART2/FINAL].

Table 3.6. Ruminant farms: Trade-off and synergies between farm performance and farm characteristics

	Australia					Ireland			Norway	United Kingdom	Comments
Farm type	Crop and livestock	Beef and sheep	Beef	Sheep	Wool	Cattle rearing	Cattle other	Sheep	Cattle	Crop and livestock	
Relationship between productivity performance and the following characteristics[1]											
Farm structure[1]	+++	+	+++	M-	M+	---	--	---	---	--	Mainly negative or average, except in Australia
Environmental sustainability	---	--	---	++	++	++	---	-	+++	--	Mainly negative
Innovation-commercialisation	M-	M+	++	M-	---	+++	+++	++	---	+++	Mainly positive or average
Technology	--	++	+++	---	--	++	+++	++	+++	+++	Mainly positive
Production diversity	---	++	+++	+++	+	+++	+++	++	+++	---	Mainly positive
Financial health	+	---	++	---	-	M+	+++	+++	+++	+++	Mainly positive
Relationship between environmental sustainability performance and the following characteristics[1]											
Farm structure[1]	--	++	---	M-	M+	---	+++	++	---	+++	Diverse
Innovation-commercialisation	M-	++	+	M-	--	++	---	--	---	M+	Mainly negative
Technology	+++	-	---	--	---	+++	---	+	+++	-	Mainly negative
Production diversity	+++	M+	---	++	+++	++	---	+	+++	+++	Mainly positive
Financial	--	++	-	--	---	M+	---	--	+++	+/-	Mainly negative or average

Note: 1. The signs and rules used to assess relationships between performance and indices are described in notes to Table 3.4.
Source: Figures and Tables in document [TAD/CA/APM/WP(2020)2/PART2/FINAL].

Table 3.7. Pig and poultry farms: Trade-off and synergies between farm performance and farm characteristics

	Denmark		United kingdom		Comments
Farm type	Rearing and fattening pig	Fattening pig	Pig[1]	Poultry	Relationships:
Relationship between productivity performance and the following characteristics[1]					
Farm structure[1]	---	---	---	---	All negative
Environmental sustainability	---	---	-/+[1]	---	Negative
Innovation-commercialisation	+++	+++	+++	+++	All positive
Technology	-	+++	+++	---	Mixed
Production diversity	M-	+++	++	++	Mostly positive
Financial health	+++	+++	++	+/-	Mostly positive
Relationship between environmental sustainability performance and the following characteristics[1]					
Farm structure[1]	+++	+++	+/-	+++	Mostly positive
Innovation-commercialisation	---	---	-/+	---	Mostly negative
Technology	-/+	---	-/+	+++	Mixed
Production diversity	-/+	---	M-	M+	Mixed
Financial	---	---	-/+	++	Mainly negative

Notes: 1. For UK pig farms, the least productive class is also the least environmentally sustainable and the most environmentally sustainable class achieves relatively good productivity levels.
See rules in notes to Table 3.4.
Source: Figures and Tables in document [TAD/CA/APM/WP(2020)2/PART2/FINAL].

3.5.4. Summary of findings by country

The detailed analysis of case studies in document [TAD/CA/APM/WP(2020)2/PART2/FINAL] allows the identification of the characteristics of the most performant farm classes in each case, based on the estimates of farm productivity and the selected indices. The main findings are summarised below.

Australia

Dairy farms in Australia show a negative correlation between the productivity and environmental sustainability of their operations. However, the majority of farms are medium productive and s environmentally sustainable. More productive dairy farms are significantly less dependent on family labour but more innovative. They employ more non-family labour and operate with larger herds. These farms also perform relatively well in terms of financial indicators as e.g. total assets and financial liquidity.

More productive crop farms in Australia are using slightly more hired labour and are more environmentally sustainable than less productive farms. Innovative crop farms are again more likely to show a higher productivity. Farms' productivity seems not necessarily correlated positively with land endowment but with the share of hired labour. More productive crop farms operate with a higher technology intensity than their less productive colleagues, *ceteris paribus*.

Beef farming in Australia is characterised by a strong positive link between production structure (i.e. larger herd size and land endowment as well as less dependent on family labour) and productivity. Least productive farms in this sector operate with a lower than average technology intensity and financial viability. Most productive beef farms are, however, less environmentally sustainable than the average beef farm in Australia. These farms are very innovative but do not necessarily operate with a higher capital and input intensity compared to medium productive beef farms.

The large majority of mixed crop-livestock farms in Australia (about 86%) produce with a high productivity and only a slightly lower than average environmental sustainability. These farms are based on an average family labour share that operate large herd sizes and relatively large land endowments. The least productive mixed crop-livestock farms in the sector use more than average hired labour input but produce with significantly less than average land endowment and livestock units. Those farms are least innovative and score relatively low on financial stability and liquidity indicators.

Most productive mixed sheep-beef farms in Australia are found to be based on a relatively high family labour endowment but also large herd sizes. These productive farms produce, however, with a significantly lower than average environmental sustainability and are only of medium innovativeness but high technology intensity. Least productive sheep-beef farms in Australia on the other side are higher than average environmentally sustainable. The majority of farms in this sector (around 74%) show a medium productivity level. However, the latter are still producing with a higher than average environmental sustainability, *ceteris paribus*.

Productive sheep meat farms in Australia are also found more environmentally sustainable than other farms in the sector. They use less family labour but produce with an average farm size. The least productive meat producing sheep farms in the sector operate with a lower than average environmental sustainability. These farms are, however, very capital intensive and least diverse. Generally, productivity differences between farms in the sector are relatively low, *ceteris paribus*.

Wool farms in Australia show more significant productivity differences across the sector. The most productive wool farms are again more environmentally sustainable. Contrary to the sheep meat sector, however, more productive wool farms are based on an average family labour endowment that operate significantly larger than average herds. A small group of least productive farms produce with a significantly lower than average environmental sustainability using a significantly higher than average amount of hired labour linked to a relatively high technology intensity.

Czech Republic

Innovative **dairy farms in the Czech Republic** are most likely more productive. Farms with a higher share of family labour and smaller farms are not *per se* operating with a higher environmental sustainability. Highly environmentally sustainable dairy farms most likely show a very diverse production structure and are most likely located in less-favoured areas with a lower than average capital intensity. Farms' capital intensity is positively correlated with herd size. The productivity of farms is correlated with herd size and the share of hired labour. Highly productive dairy farm operations can also exhibit a high level of environmental sustainability, ceteris paribus.

Chile

Highly innovative **small-scale fruit farms in Chile** are more likely to show a higher productivity. Farms that are more dependent on family labour and also smaller farms in terms of acreage do show a lower environmental sustainability of their production operations. Highly environmentally sustainable fruit farms in Chile are also very productive and most likely are located in proximity of urban centres with a higher capital intensiveness of production. The productivity of fruit farms seems to be linked to the farms' production structure at this unweighted level. Finally, the empirical results suggest that environmentally sustainable fruit farming might be correlated with higher economic productivity. However, panel data would be needed to conclude on these correlations with a higher statistical robustness.

Denmark

Innovative **dairy farms in Denmark** are most likely more productive compared to their peer group. Farms that are more dependent on family labour and comparatively smaller farms not necessarily show a higher environmental sustainability. Highly environmentally sustainable dairy farms likely show a diverse production structure but also might employ more innovative milking technology. Farms' capital intensity is not necessarily correlated with herd size, while farms' productivity is correlated with the share of hired labour, *ceteris paribus*.

Similarly, for both types of **pig farms in Denmark**, innovative farms are most likely more productive compared to their peer group, and with a higher share of family labour and smaller farms show a higher environmental sustainability. For rearing and fattening pig farms, productivity seems correlated with herd size and the share of hired labour, *ceteris paribus*. For specialised fattening pig farming, however, highly environmentally sustainable pig farms are not necessarily more diversified but operate with a lower than average capital intensity. For these fattening pig farms, productivity is correlated with herd size and the share of hired labour at unweighted class level. Finally, more sustainably producing fattening pig farms can also produce with a higher productivity, *ceteris paribus*.

Estonia

Innovative **dairy farms in Estonia** are likely to be more productive. Farms that are more dependent on family labour and smaller farms show a higher environmental sustainability based on the indicators used. Highly environmentally sustainable dairy farms are most likely located in less-favoured areas. Farms' capital intensity and the degree of specialisation are positively correlated with herd size, whereas farms' productivity is positively correlated with herd size and the share of hired labour. Dairy farms producing more sustainably are found to be less productive, ceteris paribus.

France

For **dairy farms in France**, most productive farms are less reliant on family labour and comparatively larger in terms of herd size and land endowment. These farms show an average environmental sustainability based on the measures used in the empirical analysis. Highly environmentally sustainable dairy farms are nevertheless most likely more dependent on family labour with a lower than average herd size and lower than average productivity level. The capital intensity of farms seems positively correlated with herd size, while their productivity seems correlated with herd size and the share of hired labour, *ceteris paribus*.

Innovative **crop farms in France** are more likely to show a higher productivity. Farms with a higher share of family labour and smaller farms in terms of acreage are less environmentally sustainable and less productive, *ceteris paribus*. Capital intensiveness of production is negatively correlated with the environmental sustainability of operations, whereas diverse farms are not operating with at a higher environmental sustainability level. The productivity of crop farms is linked to the farms' production structure. Finally, the empirical results at unweighted class level suggest that environmentally sustainable crop farming is positively correlated with a higher economic productivity, *ceteris paribus*.

Hungary

As in the Estonian case, innovative **crop farms in Hungary** are more likely to be productive. However, farms with a higher share of family labour and smaller farms in terms of acreage can be innovative. Environmentally sustainable crop farms are likely located in less-favoured areas whereas intensive use of capital and low level of labour intensity are positively correlated with farm size. The productivity of operations is neither linked to the size of the farms, nor to the share of family labour in total labour, or the type of ownership. These findings suggest that more environmentally sustainable crop farms are most likely less productive based on the unweighted technology classes identified.

Ireland

Innovative **dairy farms in Ireland** are most likely more productive. Farms with a higher share of family labour and smaller farms are operating with a slightly higher level of environmental sustainability relative to the average sector level. Environmentally sustainable dairy farms most likely show a diverse production structure with an average capital intensity. The productivity of farms is correlated with herd size, *ceteris paribus*. Around half of the Irish dairy sector exhibits high productivity and innovativeness, however, less than average environmental sustainability.

For **crop farming in Ireland**, a strong positive correlation between the level of innovativeness and the productivity of farming operations is also found. Those most productive crop farms are less reliant on family labour and cultivate a larger area. However, these farms are also less environmentally sustainable than the average crop farm in Ireland. About a third of all crop farms show a low productivity and also very low environmental sustainability scores based on the measures used in the empirical analysis. Those farms mainly use family labour and are smaller than average, and they are the less innovative in the crop sector.

Most productive **sheep farms in Ireland** are mainly full-time operations, which are more dependent on hired labour and highly innovative. These farms produce with a lower environmental sustainability than the sample average and a relatively high capital intensity. They score high on financial stability and liquidity. More than half of the farms in the Irish sheep sector produce with lower productivity but score significantly higher on environmental sustainability based on the measures used in the empirical analysis. About 13% of all farms were found to operate with a very low productivity and innovativeness. However, these farms, which are mainly part-time with lower input intensity, score highest on sustainability measures.

In the **"other cattle" sector in Ireland**, over half of farms produce with a medium productivity and an average level of environmental sustainability based on the measures used in the empirical analysis. The most productive cattle farms in this sector are less dependent on family labour but full-time operations with a high level of innovativeness but the lowest scores on environmental sustainability. Most environmentally sustainable cattle other farms in Ireland show a low productivity with a strong dependence on family labour but low levels of intensity and financial stability.

For **cattle rearing farms in Ireland**, most productive farms are comparatively larger in terms of herd size and land endowment. These farms show a high environmental sustainability of their production activities based on the measures used in the empirical analysis. These farms are also highly innovative. The production intensity of cattle rearing in Ireland seems positively correlated with herd size, *ceteris paribus*. The rest of the cattle rearing farms score significantly lower on environmental sustainability and also lower on productivity. Medium productive farms in the sector (nearly 10%) show significant innovation activities and financial stability. However, those farms score poor on environmental sustainability indicators.

Italy

Innovative **crop farms in Italy** are again more likely to show a higher productivity. Farms with a higher share of family labour and smaller farms in terms of acreage are not necessarily more environmentally sustainable. Highly environmentally sustainable crop farms in Italy are most likely located in lower altitudes and least likely in less-favoured areas. Capital intensiveness of production is negatively correlated with the environmental sustainability of operations, whereas diverse farms are not necessarily operating with at a higher environmental sustainability level. The productivity of crop farms is clearly linked to the farms' production structure. Finally, the empirical results at unweighted class level suggest that environmentally sustainable crop farming is not correlated with a lower or higher economic productivity.

Korea

Regarding **rice farms in Korea**, family farming and farms of a smaller size might produce more sustainably. Highly environmentally sustainable rice farms show a more diverse production structure and are most likely located in less-favoured areas with a lower than average capital intensity. However, sustainably producing rice farms can also show a relatively high productivity of their operations, *ceteris paribus*.

Norway

For **dairy farms in Norway**, farms with a higher share of family labour and comparatively smaller farms do not necessarily show a higher level of environmental sustainability based on the measures used in the empirical analysis. Highly environmentally sustainable dairy farms most likely show a more diverse production structure and are most likely located in a region favourable to dairy production. The capital intensity of farms seems positively correlated with herd size, while their productivity seems correlated with herd size and the share of hired labour. A strong share of more sustainably producing Norwegian dairy farms also exhibit a higher productivity, *ceteris paribus*.

For **crop farming in Norway**, innovative farms can be expected to be more productive compared to their peer group. Farms with a higher share of family labour and comparatively smaller farms show a lower environmental sustainability. Farms' productivity seems not necessarily correlated positively with land endowment but with the share of hired labour. For crop farms, more sustainably producing crop farms are found to show a lower productivity, *ceteris paribus*.

For specialised **cattle farming in Norway,** more innovative farms are not *per se* more productive compared to their peer group. Again, the results reveal that farms with a higher share of family labour and comparatively smaller farms show a lower environmental sustainability. Farms' capital intensity is correlated positively with herd size, while farms' productivity is not necessarily correlated with herd size and the share of hired labour. However, sustainably producing cattle farms exhibit a very high productivity at unweighted class level, *ceteris paribus*.

Sweden

For **crop farming in Sweden**, innovative farms are also more likely to be more productive and more environmentally sustainable than average. Comparatively, smaller farms and to a certain extent farms with a higher share of family labour show a lower environmental sustainability. Productivity is correlated positively with land endowment but not significantly with the share of hired labour. For crop farms in Sweden, more sustainably producing crop farms are also found to exhibit higher productivity, *ceteris paribus*.

With respect to **dairy farms in Sweden**, comparatively smaller farms achieve a higher environmental sustainability based on the variables used in the empirical analysis. However, these dairy farms are significantly less productive than other farms in the sector. Highly environmentally sustainable dairy farms most likely produce with a lower intensity but are not necessarily are more diverse. The capital intensity of farms seems positively correlated with herd size, while their productivity seems correlated with herd size but not with the share of hired labour, *ceteris paribus*. Almost half of Swedish dairy farms show a higher productivity linked to higher innovativeness. However, around 17% of all dairy farms are less innovative than the average and achieve lower productivity and environmental sustainability.

United Kingdom

Innovative **dairy farms in the United Kingdom** are likely to be more productive. Family managed and smaller farms show a higher environmental sustainability based on the indicators used. Highly environmentally sustainable dairy farms most likely produce with a lower capital and input intensity as well as a higher diversity of production. However, their innovativeness and financial stability is low, *ceteris paribus*. More than half of all dairy farms produce with a high productivity level and a slightly lower than average environmental sustainability level. Those farms are very innovative and produce with a relatively high capital intensity.

The empirical findings for **cereal farms in the United Kingdom** largely confirm the results for other crop sectors: a strong positive correlation between innovativeness and productivity. Nearly half of these farms show a high level of productivity, however, also reveal low scores on environmental sustainability based on the measures used in the empirical analysis. These farms are less dependent on family labour and of larger size with a high financial stability. A strong share of farms (nearly 43%) produce with a high environmental sustainability but a relatively low productivity. Those farms exhibit low levels of innovativeness and technology intensity.

For **mixed crop and livestock farming in the United Kingdom**, the analysis suggests that nearly a third of all farms in the sector produce with a very high productivity linked to high levels of innovativeness but significantly low levels of environmental sustainability based on the measures used in the empirical analysis. These farms score relatively high on financial stability and liquidity indicators with a capital and input intensive production. Nevertheless, a large share of likely family-dependent mixed farms in the United Kingdom (about 43%) show a high environmental sustainability and also medium productivity levels. Those farms are average innovative and capital intensive.

Similar to other **pig farming** sectors, also **for the United Kingdom** more innovative pig farms are most likely more productive compared to their peer group. Smaller farms, with a higher share of family labour, generally show a higher environmental sustainability, *ceteris paribus*. However, a small share of the farms in pig farming sector (about 7%) are highly dependent on family labour but the analysis revealed very low scores on environmental sustainability based on the measures used in the empirical analysis. Those farms show also very low levels of productivity and a low intensity of production.

For **poultry production in the United Kingdom**, the analysis revealed that most farms (around 75%) produce with a medium level of productivity and are relatively environmentally sustainable based on the measures used in the empirical analysis. These poultry farms are more dependent on family labour with a medium capital and input intensity. The most productive farms in the sector, however, score lower than average on environmental sustainability but show high levels of innovativeness. Those farms are less likely farms with a high share of family labour and operate large flocks of poultry.

4. Summary and next steps

This empirical analysis aims to measure the performance of farms taking into account fundamental differences with respect to production structure, production environmental sustainability, innovation of operations, production intensity, diversity of operations, individual characteristics as well as farm location. To reach a statistically robust classification of farms, a latent-class estimation procedure linked to a principal component analysis is employed. This approach allows the simultaneous estimation of farms' production technology and their statistical separation into different farm classes, using a number of multi-dimensional indices to adequately map the characteristics mentioned above. The production technologies and productivity patterns are then modelled and evaluated for the different kinds of farms using a flexible functional form and derived measures of farm performance.

The33 study cases analysed in this study cover thirteen countries, and a diversity of farm types, with a higher representation of specialised crop farms and dairy farms. While they do not cover all possible cases in OECD countries, they present a large diversity of agricultural conditions that supports some generalisation of findings.

Interpretation of results needs to consider the composition of the indices, which reflects data availability and may differ by country. It should be noted, however, that the core components are the same for each index, thus allowing cross-country comparability of the relationships between performance and multiple-dimensional indices.

The empirical results suggest that farms in the 33 study cases use different technologies. As a result, they can be expected to have different technical change patterns, both in terms of overall magnitudes and associated relative output and input mix changes.

According to the results, the relationship between productivity and environmental sustainability, as measured by the estimated index, which reflects the pressure on the local environment, is mostly negative for dairy, pig and poultry farms. However, this trade-off is not so widespread for ruminant and crop farms, for which strong synergies are found in several cases. Moreover, the trade-offs appear to be rather weak for crop farms.

Some strong evidence for a positive correlation between innovation and productivity at farm level across different production types is also found. Similarly, results suggest a positive correlation between the size of the farm and the productivity of agricultural operations, as well as between the labour structure (i.e. share of hired labour) and farm productivity. According to the results, innovative farms, which invest in new technologies and develop new activities, are more likely to achieve high productivity levels.

Empirical evidence with respect to farm environmental sustainability is less conclusive. There is little evidence for a positive correlation between family farming and environmental sustainability, but in many cases, environmentally sustainable farms are found to be smaller than average. Moreover, some evidence suggests, that larger farming operations can produce sustainably (except for pig and poultry farming).

The analysis points to a robust positive correlation between diversification of production and environmental sustainability, and a negative correlation between intensity of input use and environmental sustainability. However, for a further understanding of environmental sustainability performance and its drivers, it would be important to develop farm level indicators that reflect the multiple dimensions of environmental sustainability at the local and global levels. The inclusion of additional sustainability indicators in farm surveys would also be relevant for policy evaluation.[3]

The findings of this study outline farm heterogeneity and shed light on the conditions that drive the productivity and environmental sustainability performance of different types of farms in various OECD countries, as defined in this study. To be able to design more effective and efficient policies, it is important to recognise farm heterogeneity and better understand the synergies and trade-offs between productivity and environmental sustainability performance, and the circumstances leading to an optimal outcome for the sector and society. For example, the results suggest that policies that support innovation are very likely to increase productivity growth, but care should be taken that this does not happen to the detriment of environmental sustainability. Similarly, policies that facilitate structural adjustment are likely to improve productivity, but do not necessarily lead to lower environmental sustainability. The results of this study could thus help to discuss realistic futures development scenarios for each farm class, and identify most beneficial compromises for the respective sector. Policies could then be designed and implemented in a flexible way to account for specific needs and objectives.

For practical design and implementation of policies, more country-specific, in-depth analyses would be needed, for example to detect why some farms are locked in a non-productive group, or why farms with similar endowments achieve different performance.

[3] For a related discussion of farm level indicators for policy evaluation, see Poppe et al. (2016).

This study considers two main objectives of policies but there may be others, which could be considered equally using this methodology, as long as relevant indicators are available. Another consideration to keep in mind is that the farm samples used in this study mainly include commercial farms based on national statistics, and in many cases very small, hobby farms are excluded. This study does not directly analyse the linkages between policy incentives and performance, although some indicators include policy variables.

Further work aiming to strengthen the evidence basis for guiding policies intends to extend the empirical analyses to cover potential switches of farms between different technology classes over time as well as evaluate specific policy responses with respect to individual technology classes. It is of primary policy interest to provide empirical evidence on what types of farms actually switch to more productive technologies or adjust input mixes within the same technology given various production settings. This should lead to more effective and efficient design of policies.

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Annex A. Empirical and econometric framework

This Annex outlines the methodological steps applied in the analysis presented in this report to empirically identify and econometrically approximate the different technology classes for each national farm type. Furthermore, it describes the statistical procedure that has been used to represent a variety of farm classes within the number of classes determined empirically based on a combination of differences in multiple farm specific characteristics as well as multiple netput (i.e. output and input) variables (see in more detail Sauer and Morrison-Paul, 2013).

Technology model

The first part of the econometric modelling exercise consists of choosing a technology function to approximate the production process of a farm. Depending on theoretical considerations and data availability, different netput functions (e.g. production, cost, profit, distance or transformation function) and functional forms can be chosen for this purpose. From a purely theoretical perspective, (dual) functional representations that allow for the inclusion of price-related information are desirable in order to map the technical and allocative behaviour of farm managers. However, the availability of multi-output related information seems problematic for many national farm data systems. Furthermore, in order to avoid the disadvantages of normalising by one input or output as required for a distance function representation, and therefore implying econometric endogeneity problems (as the right-hand side variables are expressed as ratios with respect to the left-hand side variables, see for example Paul and Nehring, 2005), a single-output based production function representation applying a second order approximation in the form of a flexible translog functional form is preferred.

The analysis considers a production function model representing the most output producible from a given input base and existing production conditions (representing the feasible production set). In general form, this function can be written as 0 = F(Y, **X**, **T**), where Y is the farm's output, **X** is a vector of production related inputs and **T** is a vector of shift variables reflecting external production conditions. Applying the implicit function theorem F can be explicitly specified with one of the arguments on the left-hand side of the equation. Hence, the production function Y = G(**X**, **T**) can be estimated with Y as the output of the farm. This specification of the farm's production technology does not reflect endogeneity of output and input choices, but simply represents the most farm output that can technologically be produced given the levels of the other arguments of the F(.) function. A flexible functional form (second-order approximation) to accommodate various interactions among the arguments of the function including non-constant returns to scale and technical change biases approximates the production function.

This second order flexible production function model can be formulated as:

$$lnY_{it} = F(\boldsymbol{X}_{it}, \boldsymbol{T}) = \alpha_0 + \sum_{k=1}^{n} \beta_k lnX_k + \frac{1}{2}\sum_{k=1}^{n} \beta_{kk} lnX_k lnX_k + \sum_{k=1}^{n-1}\sum_{l=i+1}^{n} \gamma_{kl} lnX_k lnX_l + \delta_T T + \delta_{TT} TT + \sum_{k=1}^{n} \delta_{kT} lnX_k T \quad [1]$$

for farm i in period t with Y = total milk (crop) output, **X** is a vector of X_k inputs depending on the type of production, and a time trend T as the only component of the vector **T**. By using such a flexible functional form (here in the form of a translog functional form), observable technology differences among production units are accommodated to a certain extent as derived measures (such as output elasticities) allow for different netput mixes, hence, will differ per observation.

Unobservable technology heterogeneity is further partly accommodated by the error term in the estimation model. However, the factors leading to technology heterogeneity between farms are not directly represented by estimating [1] alone and therefore, parameter estimates might be biased (Griliches, 1957). Consequently, derived policy conclusions remain at a very general level. Recognising and evaluating heterogeneity among production systems and exploring differences in technical change developments requires a more explicit approach, consisting in estimating the technology separately for different groups or 'classes' of farms. Hence, the estimation of production technology as outlined by [1] will be combined with a probabilistic approach that allows considering simultaneously multiple characteristics of farms operating in a specific production system. This approach will result in an adequate approximation of the individual farm's production technology by considering a multitude of characteristics and therefore robustly identifying various farm groups or classes along these characteristics, for which technologies are then estimated. Hence, the estimation of the production structure as outlined in [1] is combined with the estimation of a latent class structure (see for example Greene, 2002 and 2005; Orea and Kumbhakar, 2004; Sauer and Morrison Paul, 2013).

Class identification model

Different methods can be applied to explicitly consider technological heterogeneity in farm level production (Bravo-Ureta, 1986; Tauer, 1998; Newman and Matthews, 2006; Gillespie et al., 2009; Kumbhakar et al., 2009). These differ substantially with respect to data requirements, computational intensity as well as statistical robustness. The data sample can simply be chosen based on some homogenous production criteria (e.g. a norm technology defined by the average technology in the sample) or can be divided in sub-samples to estimate different technologies based on a particular characteristic (e.g. conventional versus organic or small scale versus large scale). Methodologically more demanding, multiple criteria based cluster analysis can be applied to divide the sample according to similar farm or production related characteristics (using between versus within variances to group observations). Finally, random coefficient estimators have been used to model each farm as a unique technology based on continuous parameter variation (Alvarez et al., 2008; Greene, 2005).

The application of latent class structures (LCM) to empirically identify and estimate heterogeneous classes of observations (farms or firms) results in a separation of the data into multiple technological classes (groups or categories). This separation is based on estimated probabilities of class memberships considering multiple pre-specified criteria. Each farm is then assigned to a specific class based on these probabilities while both the estimated technological (flexible TL function) as well as the estimated probability relationships are considered (Sauer and Morrison-Paul, 2013; Balcombe et al., 2006). Hence, a latent class modelling approach overcomes possible estimation bias due to omitted variables with respect to the Class identification vector. It also effectively addresses endogeneity suspicions by a simultaneous estimation approach (i.e. a technology model and Class identification model).

In more detail, the LCM estimates a multi-nomial logit model together with the technological structure (whereas the number of parameters to be estimated might be limited by available degrees of freedom). Statistical tests can be performed to choose the most adequate number of classes/technologies to be considered. Furthermore, in addition to multiple technologies, a flexible functional form with a random effects panel estimation routine can be applied (Greene, 2005; Alvarez and delCorral, 2010) to capture farm heterogeneity over time. In this project the focus is explicitly on measuring productivity instead of unobserved inefficiency (based on a frontier specification) to reflect the specific interest in relative productivity levels between farms considering country level contextual specificities (see also Section 2).

The latent class model in a more general form can be formally denoted as the technology model (outlined in equation [1]) for class c:

$$lnY_{it} = F(\boldsymbol{X}_{it}, \boldsymbol{T}) = \left(\alpha_0 + \sum_{k=1}^{n} \beta_k lnX_k + \frac{1}{2}\sum_{k=1}^{n} \beta_{kk} lnX_k lnX_k + \sum_{k=1}^{n-1}\sum_{l=k+1}^{n} \gamma_{kl} lnX_k lnX_l + \delta_T T + \delta_{TT} TT + \sum_{k=1}^{n} \delta_{kT} lnX_k T\right) \mid c \quad [2]$$

where c denotes the Class 1ncluding farm i implying a different technology function for each class c. Assuming a normal distribution for the error term, the likelihood function for farm i at time t for class c, LF_{ict}, has the standard Ordinary Least Squares (OLS) form. The unconditional likelihood function for farm i in class c, LF_{ic}, is the product of the likelihood functions in each period t, and the likelihood function for each farm, LF_i, which is the weighted sum of the likelihood functions for each class c (with the prior probabilities of class c membership as the weights), i.e. $LF_i = \sum_c P_{ic} LF_{ic}$. These prior probabilities P_{ic} are parameterised using a multinomial logit model (MNL) consisting of indicators to describe the different dimensions of farm performances and characteristics and which are used to determine the probabilities of class memberships or separate technologies (separating or q-variables q_i).

Hence, the MNL parameters θ_c are estimated for each technology class (relative to one class serving as numeraire)

$$P_{ic} = exp(\theta_c q_i) \Big/ \left[\sum_c exp(\theta_c q_i)\right] = exp\left(\theta_{0c} + \sum_n \theta_{nc} q_{nit}\right) \Big/ \left[\sum_i exp\left(\theta_{0c} + \sum_n \theta_{nc} q_{nit}\right)\right] \quad [3]$$

where the q_{nit} denote the N q-variables/indicators for farm i in time period t.

Multi-dimensional indices

As outlined earlier farms are production units, which differ along multiple characteristics: production structure, environmental impact and sustainability, innovation behaviour, commercialisation focus, openness towards cooperation, input intensity and capital endowment, diversity of production, individual characteristics such as age or education, as well as locational conditions. A multitude of continuous or binary variables in level form can be used to directly approximate these farm characteristics as elements of the Class identification vector. However, including all those variables would lead to scaling and weighting problems and also, depending on sample size, most probably to limitations regarding the number of variables that can be considered due to missing degrees-of-freedom. Hence, multi-dimensional indexes are defined and statistically estimated, to then be incorporated as elements of the Class identification vector q.

The various indices are chosen for their potential to contribute to robustly identify and distinguish individual farms. These multi-dimensional indexes consist of different variables that measure underlying farm characteristics relevant for the dimension of the specific index to approximate. These individual index components can be equally weighted with regard to their importance for the overall index score. Further, the weights for these components could be chosen following specific expert guidance or based on trial-and-error procedures applying statistical significance criteria with respect to the parameters estimated for the g-vector elements. However, the principal components analysis (PCA) is applied as a statistically well-defined and empirically tested multivariate method to estimate significant and robust weights for the indices' components. The PCA is a method to conduct a conceptual factor analysis that will then create statistically robust indexes based on different variables (for an overview of PCA, see Jackson, 2003 or Afifi et al., 2012).

PCA is a multivariate statistical technique used for data reduction. The leading eigenvectors (i.e. principal components) from the eigen decomposition of the correlation or covariance matrix of the variables (here index components) describe a series of uncorrelated linear combinations of the variables that contain most of the variance. In addition to data reduction, the eigenvectors from a PCA can be further inspected to learn more about the underlying structure of the data. Hence, in a first step such a PCA is run for each farm related dimension (e.g. production structure) resulting in the eigenvalues for the individual components (e.g. share of family labour and area or herd size). The eigenvalue for each component represents how much of variance the component explains (i.e. factor loading). Subsequently, the factor loadings are used to calculate the index score for each observation via an optimally-weighted linear combination of the factor scores for the individual components- characteristics.

Accordingly, up to seven different farm indices are defined and estimated for each observation of the respective sample using the deviations of each index component from the sample mean to adequately consider differences between member countries' farm structures and conditions (For example, an average family farm in Italy in terms of family labour share may be very different from an average family farm in terms of family labour share located in Estonia). Scaling issues between different components (e.g. share of family labour versus herd size or acreage) are further addressed by calculating the z-score based deviations for these components, which are then used for the PCA based index creation following the statistical procedure outlined above. For subsequent analyses up to seven multi-dimensional indexes are chosen to identify and measure class membership per farm and year. These indexes are estimated as outlined above subject to type of production and data availability. The significance and the posterior probabilities of resulting q-variable coefficient's estimates are evaluated for the individual farm classes. Furthermore, statistical tests are applied to robustly determine the number of classes (for example, the Akaike Information Criterion/Schwarz and Bayesian information criterion [AIC/SBIC] tests, described in Greene, 2005) by testing down (i.e. to verify if fewer classes would be statistically supported).

Full model specifications

The combined (technology and Class identification) model can be estimated in a cross-sectional or a panel form whereas for the full-model specification a random effects based estimator can be applied (Sauer and Morrison-Paul, 2013; Greene, 2005). The panel data related specification of the model is then:

$$ln y_{it|c} = \alpha_0 + \sum_{k=1}^{n} \beta_{k,c} ln x_{kit} + \frac{1}{2}\sum_{k=1}^{n} \beta_{kk,c} ln X_{kit} ln X_{kit} + \sum_{k=1}^{n-1}\sum_{l=k+1}^{n} \gamma_{kl,c} ln x_{kit} ln x_{lit} + \delta_{T,c} t_{it} + \delta_{TT,c} t_{it} t_{it} + \sum_{k=1}^{n} \delta_{kT,c} ln x_{kit} t_{it} + \varepsilon_{it|c} \quad [4]$$

with farm i in time period t and class c and ε denoting an independent and identically distributed (iid) stochastic term. For an alternative specification each observation is considered as a separate entity and the model is then estimated as a cross-sectional specification. This model allows farms to switch between technology classes and hence, changes in production systems over the time period can be approximated.

$$lny_{i|c} = \alpha_0 + \sum_{k=1}^{n} \beta_{k,c} lnx_{ki} + \frac{1}{2}\sum_{k=1}^{n} \beta_{kk,c} lnX_{ki} lnX_{ki} + \sum_{k=1}^{n-1}\sum_{l=k+1}^{n} \gamma_{kl,c} lnx_{ki} lnx_{li} + \delta_{T,c} t_i + \delta_{TT,c} t_i t_i + \sum_{k=1}^{n} \delta_{kT,c} lnx_{ki} t_i + \varepsilon_{i|c}$$

[5]

with farm i, class c and ε denoting again the independent and identically distributed (iid) stochastic term.

As both model components (technology related and Class identification related) are simultaneously estimated the probabilities P_{ic} (see equation [3]) are functions of the parameters of the MNL model and the log-likelihoods LF_{ic} are functions of the technology parameters for class c farms. Accordingly, the overall likelihood function for farm i in class c consists of both sets of parameters whereas the overall log-likelihood function for the complete model is maximised based on the sum of the individual log-likelihood functions. Finally, due to degrees-of-freedom problems related to the parameter intensive LCM specification, as done in Sauer and Morrison-Paul (2013), the models in [4] and [5] are estimated as a reduced (or constrained) form approximation to the underlying translog functional form. Thus, the resulting (first-order and own second-order) elasticities represent the average contributions of each input to production, as well as overall technical change and returns to scale for each class. To accommodate and measure the second-order effects involving input technical change biases and substitution, the full translog form for the full sample and the separate classes will also be estimated. If the distinctions among classes capture key differences in technology, as found for all country cases investigated, the elasticities for the constrained and fully flexible functional forms will be comparable, but incorporating the interaction terms will allow assessment of cross effects between inputs.

Performance measures

Several performance measures derived from the technology related component of the combined estimation model outlined in equation [3] and [4] or [5] are explored. In a first step, the relative *levels of productivity* are estimated among the different identified farm classes based on the predicted output levels for a given amount of inputs at the sample means (Alvarez and Corral, 2010). The hypothetical productivity levels are then estimated for each class assuming an alternative technology and the differences between real and hypothetical technologies are compared. In a second step, productivity dynamics, more commonly noted as *technical change*, is considered per class and technology. Such technical change is measured by shifts in the overall production frontier over time using the output elasticity with respect to T

$$\epsilon_{y,T\,|c} = \frac{\partial lnY}{\partial T}\,|c = \delta_{T,c} + 2 * \delta_{TT,c} t_i + \sum_{k=1}^{n} \delta_{kT,c} lnx_{ki}$$

[6]

Technical change is estimated for each class at the sample means using the estimated parameters and the elasticity formula given by equation [6]. The hypothetical technical change rate is also estimated for each class measuring the alternative technology at each class related sample means. Finally, the differences between real and hypothetical rates of technical change are then compared. These two core measures deliver evidence on the distribution of productivity and technical change over different farm classes and also allow inferences with regard to potential productivity increases as well as technical change rate accelerations by facilitating farms' switch to more productive technologies over time.

The next analytical performance measure that is derived from the constrained flexible and fully flexible TL production functions are *first-order elasticities* with respect to the primary output (e.g. dairy or crop related output) for each class c. These first-order elasticities in terms of primary output Y represent the (proportional) shape of the production function (given other inputs) for input X_k - or input contributions to primary output respectively. The estimated output elasticity with respect to input k

$$\epsilon_{y,k\,|c} = \left(\frac{\partial Y}{\partial X_k} * \left[\frac{X_k}{Y}\right]\right)|c = \beta_{k,c} + \frac{1}{2}\beta_{kk,c} lnx_{ki} + \sum_{l=k+1}^{n} \gamma_{kl,c} lnx_{li} + \delta_{kT,c} t_i \quad [7]$$

would be expected to be positive, with its magnitude representing the (proportional) marginal productivity of X_k. Second-order own-elasticities may be computed to confirm that the curvature of these functions satisfies regularity conditions; the marginal productivity is expected to increase at a decreasing rate, so second derivatives with respect to X_k are expected to be negative to fulfil the concept of a well-defined functional representation of the production problem under consideration. Input elasticities give insight into the relative productivity of different inputs given the production context. The policy maker is, hence, able to evaluate the marginal contribution of each input to overall production at farm and sectoral levels and therefore its relative importance for the type of production. Linked to the technology class related analysis performed here, input elasticities enable policy makers to evaluate different technologies with respect to their relative input intensity and dependence.

Based on the derived first-order elasticities *returns to scale* are estimated as a linear combination of the input elasticities with respect to the primary output. These are simply defined as the sum of the input elasticities as follows

$$s\epsilon_{y,X\,|c} = \sum_{k=1}^{n}\left(\frac{\partial Y}{\partial X_k} * \left[\frac{X_k}{Y}\right]\right)|c = \sum_{k=1}^{n}\left(\beta_{k,c} + \frac{1}{2}\beta_{kk,c} lnx_{ki} + \sum_{l=k+1}^{n} \gamma_{kl,c} lnx_{li} + \delta_{kT,c} t_i\right) \quad [8]$$

Returns to scale allow for empirically informed inferences about the “cost of scale” with respect to a type of production at farm and sectoral level. Increasing returns to scale suggest extending the production of the specific output to increase the profitability of production via lower average costs. Decreasing returns suggest the opposite, i.e. reducing the scale of production to increase profitability via lower average costs, and finally constant returns suggest that the actual scale of production is approximately near the optimal — most efficient — point of scale for the specific firm or sector (*ceteris paribus*). Policy makers are therefore able to design programmes and measures that are more efficient, to more effectively enable economies of scale where relevant based on these measures. As a result of the simultaneously estimated farm classes, policy makers are able to design such programmes more efficiently as the latter are also farm class specific depending on the Class identification vector (see above).

Finally, *second-order or cross-elasticities* with respect to input substitution as well as input-using or input-saving technical change (biases) can be estimated based on the flexible TL production function. These performance measures involve second-order derivatives such as, for input substitution,

$$\epsilon_{k,l\,|c} = \left(\frac{\partial^2 Y}{\partial X_k \partial X_l}\right) * \left[\frac{X_l}{\left(\frac{\partial Y}{\partial X_k}\right)}\right] |c = \left(\frac{\partial MP_{Y,k}}{\partial X_l}\right) * \left[\frac{X_l}{MP_{Y,k}}\right] |c = \gamma_{kl,c} \quad [9]$$

where $MP_{Y,k}$ refers to the marginal product of Y with respect to X_k. The elasticity in [9] represents the extent to which the marginal product of X_k changes due to changes in X_l. The corresponding technical change measure

$$\epsilon_{k,T\ |c} = \left(\frac{\partial^2 Y}{\partial X_k \partial T}\right) * \left[\frac{1}{\left(\frac{\partial Y}{\partial X_k}\right)}\right] |c\ = \left(\frac{\partial MP_{Y,k}}{\partial T}\right) * \left[\frac{1}{MP_{Y,k}}\right] |c\ =\ \delta_{kT,c} \qquad [10]$$

represents the bias in technical change, i.e. whether such technical change is input k-using or input k-saving. Accordingly, the input k intensity for farms in class c is increasing or decreasing over the time period investigated. Finally, returns to scale (see equation [8]) can be analysed whether they are increasing or decreasing over time (depending on technical change) for each identified class of farms following:

$$s\epsilon_{y,X,T\ |c} = \frac{\partial \sum_{k=1}^{n}\left(\frac{\partial Y}{\partial X_k} * \left[\frac{X_k}{Y}\right]\right)}{\partial T}\ |c\ = \sum_{k=1}^{n}\left(\ \delta_{kT,c}\right) \qquad [11]$$

These second-order performance measures rely on the unconstrained flexible functional form and deliver empirical evidence on the input substitution patterns and technical change biases per class. Policy makers might want to know which type of farm is most effective in substituting less environmentally sustainable inputs by more environmentally sustainable inputs as a reaction to specific incentives or regulatory measures.

Annex B. Literature review

Since the seminal work by Aigner, Lovell, and Schmidt (1977), and Meeusen and van Den Broeck (1977), stochastic production frontiers have become a popular tool to measure technologies and efficiencies of individual producers. In recent years, two aspects regarding firm heterogeneity in parametric efficiency analysis became increasingly important. First, traditional models are not able to distinguish inefficiency from unobserved firm-specific technological heterogeneity. Greene (2005, 2004) extends existing fixed and random effects formulations by adding firm-specific constant terms to the stochastic frontier models. By this means, these so called 'true' fixed or random effects models capture unobserved heterogeneity in the intercept. Second, different groups of farms or firms may use different technologies so that farm or firm heterogeneity cannot be captured by the intercept only and the estimation of one common production frontier would be inappropriate. Specifically, assuming a homogeneous technology when heterogeneous technologies exist will yield biased estimates of the technological characteristics and productivity or efficiency.

If the sample separation is known, separate technological frontiers can easily be estimated. For example, Battese, Rao, and O'Donnell (2004) estimate separate production frontiers for garment firms in different regions of Indonesia and identify technology gaps between regions using a metafrontier approach. Several studies accounting for endogenous technology choice exist (see, for example, Key and McBride (2003) on the use of production contracts in the US hog sector or Kumbhakar, Tsionas, and Sipiläinen (2009) on the choice between organic and conventional farming in Finland). In many cases, however, sample separation information is not available a priori. Latent class models (also referred to as mixture models) can then be used to simultaneously classify groups and estimate the respective technologies.

Caudill (2003) introduces an expectation-maximisation algorithm to estimate a mixture of stochastic cost frontiers for the US banking sector. Two distinct technology classes are identified and comparisons show that institutions associated with one regime are considerably larger than their counterparts, i.e. technology varies with firm size. Greene (2005) suggests a maximum likelihood latent class stochastic frontier model using sample separation information where the inefficiency term varies freely over time. This approach is compared to alternative models that assume homogeneous technologies in an application to data on the US banking industry. Orea and Kumbhakar (2004) propose a slight variation of the Greene (2005) model to let the inefficiency term vary systematically over time, arguing that this modification fully exploits the heterogeneous panel structure of the data. The model is demonstrated using Spanish banking data which is shown to support four distinct technology classes. Further studies using the latent class frontier framework in the banking sector are Koetter and Poghosyan (2009), Poghosyan and Kumbhakar (2010), and Danquah and Quartey (2015).

Apart from the banking sector, latent class production frontier is commonly applied in the energy sector (Llorca, Orea and Pollitt 2014; Orea and Jamasb 2017; Cullmann 2012; Lin and Du 2014; Agrell et al., 2014). For example, Cullmann (2012) recognises that the incentive regulation of German electricity distributors depends on benchmarking, which separates large and small distributors *ex ante*. Data on regional and local German electricity distributors are used to fit a parametric input distance function as both a true random effects frontier and a latent class frontier. The results show that even though one class mainly consists of considerably larger companies than the other class, the correlation between the efficiencies obtained from the two models is quite low. Orea and Jamasb (2017) combine the latent class frontier with the zero inefficiency model by Kumbhakar, Parmeter, and Tsionas (2013), allowing for the identification of both behavioural differences (fully efficient firms vs. inefficient firms) and technological differences between firms. The model is applied to Norwegian distribution network utilities for the period 2004–11, and the results show that both the latent class frontier and the zero-inefficiency model result in biased estimates for the efficiency scores. Further latent class technology identification studies are found in the health sector (Barros, de Menezes and Vieira, 2013; Besstremyannaya, 2011), higher education (Agasisti and Johnes, 2015), transportation (Obeng, 2013; Barros, 2009), sports (Jewell, 2017), and cross-sector industries (Becchetti and Trovato, 2011).

Latent class stochastic production or frontier models have also widely been applied in the agricultural sector. Many of these studies distinguish between extensive and intensive dairy production. For example, Alvarez and del Corral (2010) estimate a latent class production frontier to study the technological differences between extensive and intensive dairy farms in Spain using data on 130 dairy farms over the period 1999–2006. On average, 40% of farms are classified as being intensive. Even if farms are allowed to switch between the classes over time, no trend towards a more or less intensive sector is observable. A comparison between the two groups shows that the intensive technology is more productive than the extensive one and that intensive farms are more technically efficient. A decomposition of productivity growth further indicates that the technology of intensive farms was characterised by a larger technical progress compared to the technology of extensive farms, and that extensive farms experienced negative scale and efficiency changes over time.

Kellermann and Salhofer (2014) compare dairy farms operated on grassland to dairy farms using fodder-crops from arable land in Southern Germany from 2000 to 2008. While this sample separation is assumed a priori, a latent class model is used to allow for potential differences in technologies within these two groups. The different sub-groups are associated with extensive and intensive dairy production. The findings suggest that permanent grassland farms are not generally less productive than fodder-crop farms, but extensively operated farms lag behind both in productivity and in productivity change. Orea, Perez and Roibas (2015) employ the stochastic frontier latent class model to assess the effect of land fragmentation on technology choice between extensive and intensive dairy farming in Spain. Using an unbalanced panel of 148 farms over a 13-year period from 1999–2011, they find that the number of plots reduces the Technical Efficiency (TE) of extensive farms but not for intensive ones. Based on this result and further simulations, they conclude that the impact of land fragmentation on farm productivity is larger for extensive farms.

Alvarez, del Corral and Tauer (2012) explicitly compare a latent class technology model for New York dairy farms from 1993 to 2004 and a two-stage model where sample separation is based on a priori information on the milking system applied. The latent class analysis separates the sample into one class that is dominated by farms using a parlour milking technology, and a second class that is dominated by farms using a stanchion milking technology. The classes based on milking systems show a more similar production technology than the classes identified by the latent class model. The authors conclude that there are additional characteristics that are important to differentiate the sample farms and suggest that the latent class modelling approach seems the superior method for separating heterogeneous technologies.

There are other empirical studies focusing on the agricultural sector: Wen and Stefanou (2007) use farm household data from India (1975-1984) to investigate the relationship between social learning and production behaviour in castor production. The class separation variables show that the socio-economic status, reflected by the caste rank, explains class membership in the stochastic latent class frontier model applied. The authors therefore conclude that social learning influences the choice of technology. Further, improvements in efficiency over time are attributed to the process of social learning. Felthoven, Horrace, and Schnier (2009) use the latent class frontier approach to explore capacity utilisation in multi-species fisheries. The analysis shows that without considering production heterogeneity, capacity estimates are misleading. Baráth and Fertő (2015) apply a latent class approach to identify heterogeneous technologies among specialised crop farms in Hungary over the period 2001-09. Two classes consisting of roughly equal numbers of farms are identified that mainly differ in terms of size whereas the technology pertaining to the larger farms is shown to be more productive. Recently, Martinez Cillero et al. (2018) use a latent class stochastic model to account for technology heterogeneity in the Irish beef sector. They find decoupled payments affect farms' efficiencies for only two of three identified technologies.

In a quite different context, Hassine and Kandil (2009) use a latent class production frontier to account for cross-country heterogeneity in farming production technologies. Using country-level panel data from nine southern Mediterranean and five EU Mediterranean countries covering the period 1990–2005, they find a positive and statistically significant effect of trade openness on agricultural productivity growth and poverty alleviation. Variables such as fertiliser use and average farm size provide useful information for the classification of the sample into four distinct technology classes. Similarly, Mekonnen et al. (2015) apply the latent class model to country-level data from 85 low- and middle-income countries for the period 2004–11 to explain the relationship between agricultural innovation systems (such as mobile phone subscriptions or R&D activities) and technical efficiency. In a second step, they employ the metafrontier approach to compare efficiency between countries across the different technological classes. The results provide some evidence that the contribution of different innovation systems to technical efficiency varies across technology classes.

Agrell and Brea-Solís (2017) recently wrote a critical review of latent class production function or frontier models, focussing on electricity distribution operations. They argue that benchmarking based on latent class frontier models assumes that different technologies indeed exist and that the observations covered by certain classes are not outliers. To address potential problems, they compare the classes identified by the latent class approach to results from a non-parametric outlier detection method based on the super-efficiency concept using data from Swedish electricity distributors over the period 2000-06. The results show that the smallest technology class mainly consists of observations that have been detected as outliers. Even if the authors conclude that this is an important caveat of latent class modelling, it has to be emphasised that this study refers to energy distributors only and the findings may not be transferable to other sectors. Finally, it should be noted that an array of alternative stochastic frontier models with consideration of sample heterogeneity exists. These include the random coefficient model (Tsionas 2002; Greene 2005), which can be viewed as a generalisation of the latent class model, Markov-switching stochastic frontier models (Tsionas and Kumbhakar, 2004), and threshold stochastic frontier models (Yélou, Larue and Tran, 2010).

Apart from stochastic frontier analysis, latent class has also been applied to average production functions. Sauer and Paul (2013) employ a transformation function in the latent class framework, where different technologies are classified based on production intensity, extent of organic production, input intensity of production, and degree of specialisation. Applied to a sample of Danish dairy farms covering the years 1986–2005, they find that the data supports three distinct classes of technologies. The results further show that larger and more capital farms experience greater technical progress and become more specialised over time. Chaffai and Plane (2017) estimate a latent class production function for Egyptian industrial firms (Garments, Textiles, Food and Processing, Metal Products, and Chemistry) for the period 2003–08 and find two distinct technologies over five investigated industries.

Annex C. Supporting tables

Table A C.1. Main characteristics of technology classes, dairy farms

Country case	Class 1	Class 2	Class 3
Australia			
Distribution of farms (%)[1]	20	5	76
Relative productivity (%)[2]	100	23	35
Technical change (% per year)	1.74	2.86	1.79
Czech Republic			
Distribution of farms (%)[1]	34	32	34
Relative productivity (%)[2]	100	16	8
Technical change (% per year)	2.06	0.37	0.97
Denmark			
Distribution of farms (%)[1]	67	16	17
Relative productivity (%)[2]	100	94	53
Technical change (% per year)	1.78	2.97	2.02
Estonia			
Distribution of farms (%)[1]	83	17	
Relative productivity (%)[2]	7	100	
Technical change (% per year)	2.16	0.35	
France			
Distribution of farms (%)[1]	21	52	27
Relative productivity (%)[2]	100	80	54
Technical change (% per year)	-0.56	-0.05	-0.09
Ireland			
Distribution of farms (%)[1]	51	8	41
Relative productivity (%)[2]	100	45	49
Technical change (% per year)	0.28	0.56	-0.39
Norway			
Distribution of farms (%)[1]	65	16	19
Relative productivity (%)[2]	100	47	94
Technical change (% per year)	2.52	-0.41	0.49
Sweden			
Distribution of farms (%)[1]	36	47	17
Relative productivity (%)[2]	35	100	35
Technical change (% per year)	1.06	0.72	2.67
United Kingdom			
Distribution of farms (%)[1]	28	55	18
Relative productivity (%)[2]	46	100	56
Technical change (% per year)	2.31	1.96	0.32

Note: 1. Share of farms in a class as a percentage of all sample farms.
2. Productivity level of farms in a class as a percentage of productivity level in the most productive class.
Source: Tables in document [TAD/CA/APM/WP(2020)2/PART2/FINAL].

Table A C.2. Main characteristics of technology classes, crop farms

Country case	Class 1	Class 2	Class 3	Class 4
Australia				
Distribution of farms (%)[1]	88	12		
Relative productivity (%)[2]	100	31		
Technical change (% per year)	0.24	-0.72		
Chile (Small-scale fruit farms)				
Distribution of farms (%)[1]	45	36	19	
Relative productivity (%)[2]	100	7	22	
Technical change (% per year)	NA	NA	NA	
France				
Distribution of farms (%)[1]	55	25	9	12
Relative productivity (%)[2]	91	36	87	100
Technical change (% per year)	1.24	- 2.39	0.77	- 2.43
Hungary				
Distribution of farms (%)[1]	28	22	50	
Relative productivity (%)[2]	100	46	94	
Technical change (% per year)	5.00	2.01	3.99	
Ireland				
Distribution of farms (%)[1]	33	34	33	
Relative productivity (%)[2]	100	29	52	
Technical change (% per year)	0.10	- 1.22	- 0.92	
Italy				
Distribution of farms (%)[1]	52	7	42	
Relative productivity (%)[2]	100	36	59	
Technical change (% per year)	- 0.68	1.78	1.50	
Korea (rice farms)				
Distribution of farms (%)[1]	58	33	9	
Relative productivity (%)[2]	83	100	46	
Technical change (% per year)	1.44	1.74	- 1.37	
Norway				
Distribution of farms (%)[1]	42	45	14	
Relative productivity (%)[2]	100	61	66	
Technical change (% per year)	2.28	1.47	0.93	
Sweden				
Distribution of farms (%)[1]	25	34	41	
Relative productivity (%)[2]	74	100	24	
Technical change (% per year)	3.15	4.89	2.15	
United Kingdom (cereal farms)				
Distribution of farms (%)[1]	49	8	43	
Relative productivity (%)[2]	100	85	49	
Technical change (% per year)	1.11	3.27	- 2.39	

Note: NA: Not available. 1. Share of farms in a class as a percentage of all sample farms.
2. Productivity level of farms in a class as a percentage of productivity level in the most productive class.
Source: Tables in document [TAD/CA/APM/WP(2020)2/PART2/FINAL].

Table A C.3. Main characteristics of technology classes, various livestock farms

Country case	Class 1	Class 2	Class 3
Australian crop-livestock farms			
Distribution of farms (%)[1]	86	5	8
Relative productivity (%)[2]	100	77	32
Technical change (% per year)	0.04	0.55	- 0.75
Australian beef-sheep farms			
Distribution of farms (%)[1]	9	17	74
Relative productivity (%)[2]	15	100	40
Technical change (% per year)	- 0.37	0.20	- 1.11
Australian beef farms			
Distribution of farms (%)[1]	68	22	10
Relative productivity (%)[2]	32	100	10
Technical change (% per year)	- 0.89	0.79	- 3.71
Australian sheep meat farms			
Distribution of farms (%)[1]	74	10	16
Relative productivity (%)[2]	100	81	88
Technical change (% per year)	1.44	3.19	3.85
Australian wool farms			
Distribution of farms (%)[1]	80	3	16
Relative productivity (%)[2]	100	40	68
Technical change (% per year)	0.56	0.13	0.99
Danish rearing and fattening pig farms			
Distribution of farms (%)[1]	48	9	43
Relative productivity (%)[2]	46	26	100
Technical change (% per year)	1.33	0.63	1.87
Danish fattening pig farms			
Distribution of farms (%)[1]	19	60	21
Relative productivity (%)[2]	100	50	30
Technical change (% per year)	2.08	1.84	1.61
Irish cattle rearing farms			
Distribution of farms (%)[1]	27	9	64
Relative productivity (%)[2]	100	76	60
Technical change (% per year)	1.07	0.80	2.15
Irish “cattle other” farms			
Distribution of farms (%)[1]	52	27	22
Relative productivity (%)[2]	41	19	100
Technical change (% per year)	0.76	2.68	0.18
Irish sheep farms			
Distribution of farms (%)[1]	25	38	38
Relative productivity (%)[2]	100	46	50
Technical change (% per year)	- 0.81	0.26	- 1.06

Norwegian cattle farms			
Distribution of farms (%)[1]	81	19	
Relative productivity (%)[2]	100	88	
Technical change (% per year)	1.56	- 1.20	
UK crop-livestock farms			
Distribution of farms (%)[1]	28	29	43
Relative productivity (%)[2]	100	29	46
Technical change (% per year)	0.94	- 1.96	2.10
UK pig farms			
Distribution of farms (%)[1]	28	65	7
Relative productivity (%)[2]	100	73	22
Technical change (% per year)	3.17	0.45	3.56
UK poultry farms			
Distribution of farms (%)[1]	21	4	75
Relative productivity (%)[2]	100	19	64
Technical change (% per year)	3.30	5.28	1.39

Note: 1. Share of farms in a class as a percentage of all sample farms.
2. Productivity level of farms in a class as a percentage of productivity level in the most productive class.
Source: Tables in document [TAD/CA/APM/WP(2020)2/PART2/FINAL].

Table A C.4. Dairy farms: Productivity gains if most productive technology adopted

	Class 1	Class 2	Class 3	All classes
Australia	Most productive	Least productive	Medium productive	
Share in sample farms (%)	20	5	76	100
Productivity level (EUR per farm): A. historical	674 837	156 788	239 492	320 932
B. if most productive technology adopted	674 837	495 966	587 930	600 641
Change in productivity B/A (%)	0.0	216.3	145.5	87.2
Czech Republic	Most productive	Medium productive	Least productive	
Share in sample farms (%)	34	32	34	100
Productivity level (EUR per farm): A. historical	740 489	121 463	60 893	311 109
B. if most productive technology adopted	740 489	323 957	165 440	411 964
Change in productivity B/A (%)	0.0	166.7	171.7	32.4
Denmark	Most productive	Medium productive	Least productive	
Share in sample farms (%)	67	16	17	100.0
Productivity level (EUR per farm): A. historical	695 809	655 091	367 261	633 191
B. if most productive technology adopted	695 809	578 348	463 438	637 353
Change in productivity B/A (%)	0.0	-11.7	26.2	0.7
Estonia	Least productive	Most productive		
Share in sample farms (%)	83	17		58
Productivity level (EUR per farm): A. historical	30 056	403 407		94 168
B. if most productive technology adopted	126 033	403 407		173 664
Change in productivity B/A (%)	319.3	0.0		84.4
France	Most productive	Medium productive	Least productive	
Share in sample farms (%)	21	52	27	100
Productivity level (EUR per farm): A. historical	169 437	135 990	91 133	130 723
B. if most productive technology adopted	169 437	149 851	126 792	147 646
Change in productivity B/A (%)	0.0	10.2	39.1	12.9
Ireland	Most productive	Least productive	Medium productive	
Share in sample farms (%)	51	8	41	100
Productivity level (EUR per farm): A. historical	245 134	110 494	120 351	183 461
B. if most productive technology adopted	245 134	150 678	142 729	195 788
Change in productivity B/A (%)	0.0	36.4	18.6	6.7
Norway	Most productive	Least productive	Medium productive	
Share in sample farms (%)	65	16	19	100
Productivity level (EUR per farm): A. historical	84 379	39 383	79 705	76 169
B. if most productive technology adopted	84 379	52 025	76 950	77 696
Change in productivity B/A (%)	0.0	32.1	-3.5	2.0
Sweden	Least productive	Most productive	Medium productive	
Share in sample farms (%)	36	47	17	100
Productivity level (EUR per farm): A. historical	75 584	216 967	76 451	142 041
B. if most productive technology adopted	211 356	216 967	161 894	205 530
Change in productivity B/A (%)	179.6	0.0	111.8	44.7
United Kingdom	Least productive	Most productive	Medium productive	
Share in sample farms (%)	28	55	18	100
Productivity level (EUR per farm): A. historical	133 319	289 971	161 968	224 335
B. if most productive technology adopted	302 959	289 971	285 230	292 726
Change in productivity B/A (%)	127.2	0.0	76.1	30.5

Note: Assuming the technology of the most productive farm is also the best for other farm classes.
Source: Tables in document [TAD/CA/APM/WP(2020)2/PART2/FINAL].

Table A C.5. Crop farms: Productivity gains if most productive technology adopted

	Class 1	Class 2	Class 3	Class 4	All classes
Australia	Most productive	Least productive			
Share in sample farms (%)	87.6	12.4			100.0
Productivity level (EUR per farm): A. historical	406 185	124 439			226 205
B. if most productive technology adopted	406 185	258 943			274 896
Change in productivity B/A (%)	0.0	108.1			21.5
Chile	Most productive	Least productive	Medium productive		
Share in sample farms (%)	44.6	36.2	19.2		100.0
Productivity level (EUR per farm): A. historical	8 380	570	1 852		4 299
B. if most productive technology adopted	8 380	3 448	6 434		6 221
Change in productivity B/A (%)	0.0	504.7	247.4		44.7
France	Medium productive	Least productive	Medium productive	Most productive	
Share in sample farms (%)	55.3	24.6	8.5	11.6	100.0
Productivity level (EUR per farm): A. historical	147 931	58 029	142 130	162 999	127 070
B. if most productive technology adopted	117 466	81 520	59 427	162 999	108 971
Change in productivity B/A (%)	-20.6	40.5	-58.2	0.0	-14.2
Hungary	Most productive	Least productive	Medium productive		
Share in sample farms (%)	28	22	50		105 141
Productivity level (EUR per farm): A. historical	123 355	57 234	116 021		126 339
B. if most productive technology adopted	123 355	86 131	145 702		20.2
Change in productivity B/A (%)	0.0	50.5	25.6		105 141
Ireland	Most productive	Least productive	Medium productive		
Share in sample farms (%)	33.2	34.1	32.7		100.0
Productivity level (EUR per farm): A. historical	195 166	56 982	102 317		117 684
B. if most productive technology adopted	195 166	190 175	124 517		170 362
Change in productivity B/A (%)	0.0	233.7	21.7		44.8
Italy	Most productive	Least productive	Medium productive		
Share in sample farms (%)	51.5	7	41.5		100.0
Productivity level (EUR per farm): A. historical	46 102	16 654	27 266		36 223
B. if most productive technology adopted	46 102	26 226	36 396		40 682
Change in productivity B/A (%)	0.0	57.5	33.5		12.3
Korea (rice	Medium productive	Most productive	Least productive		
Share in sample farms (%)	57.9	33.3	8.8		100.0
Productivity level (EUR per farm): A. historical	4 978	5 985	2 759		5 118
B. if most productive technology adopted	5 082	5 985	2 658		5 170
Change in productivity B/A (%)	2.1	0.0	-3.7		1.0
Norway	Most productive	Least productive	Medium productive		
Share in sample farms (%)	41.8	44.6	13.6		100.0
Productivity level (EUR per farm): A. historical	56 288	34 422	37 344		43 959
B. if most productive technology adopted	56 288	37 177	55 801		47 698
Change in productivity B/A (%)	0.0	8.0	49.4		8.5
Sweden	Medium productive	Most productive	Least productive		
Share in sample farms (%)	25.1	34.3	40.6		100.0
Productivity level (EUR per farm): A. historical	159 276	215 005	51 195		134 510
B. if most productive technology adopted	105 103	215 005	97 548		139 732
Change in productivity B/A (%)	-34.0	0.0	90.5		3.9
United Kingdom	Most productive	Medium productive	Least productive		
Share in sample farms (%)	49.1	8	42.9		100.0
Productivity level (EUR per farm): A. historical	273 160	232 477	134 407		210 380
B. if most productive technology adopted	273 160	185 471	167 553		220 839
Change in productivity B/A (%)	0.0	-20.2	24.7		5.0

Note: Assuming the technology of the most productive farm Class 1s also the best for other farm classes.
Source: Tables in document [TAD/CA/APM/WP(2020)2/PART2/FINAL].

Table A C.6. Other livestock farms: Productivity gains if most productive technology adopted

Country case	Class 1	Class 2	Class 3	All classes
Australian crop-livestock farms	Most productive	Medium productive	Least productive	
Share in sample farms (%)	86	5	8	100
Productivity level (EUR per farm): A. historical	244 639	189 560	78 666	227 778
B. if most productive technology adopted	244 639	247 079	179 811	239 323
Change in productivity B/A (%)	0.0	30.3	128.6	5.1
Australian beef-sheep farms	Least productive	Most productive	Medium productive	
Share in sample farms (%)	9	17	74	100
Productivity level (EUR per farm): A. historical	32 340	219 514	87 887	105 937
B. if most productive technology adopted	93 851	219 514	136 062	146 911
Change in productivity B/A (%)	190.2	0.0	54.8	38.7
Australian beef farms	Medium productive	Most productive	Least productive	
Share in sample farms (%)	68	22	10	100
Productivity level (EUR per farm): A. historical	146 912	460 634	44 318	204 948
B. if most productive technology adopted	405 941	460 634	248 119	401 505
Change in productivity B/A (%)	176.3	0.0	459.9	95.9
Australian sheep meat farms	Most productive	Least productive	Medium productive	
Share in sample farms (%)	74	10	16	100
Productivity level (EUR per farm): A. historical	112 411	90 686	98 890	92 141
B. if most productive technology adopted	112 411	72 176	87 822	90 290
Change in productivity B/A (%)	0.0	-20.4	-11.2	-2.0
Australian wool farms	Most productive	Least productive	Medium productive	
Share in sample farms (%)	80	3	16	100
Productivity level (EUR per farm): A. historical	105 933	42 880	72 545	98 440
B. if most productive technology adopted	105 933	42 709	77 023	99 169
Change in productivity B/A (%)	0.0	-0.4	6.2	0.7
Danish rearing and fattening pig farms	Medium productive	Least productive	Most productive	
Share in sample farms (%)	48	9	43	100
Productivity level (EUR per farm): A. historical	626 704	352 156	1360 862	919 700
B. if most productive technology adopted	614 048	347 329	1360 862	913 200
Change in productivity B/A (%)	-2.0	-1.4	0.0	-0.7
Danish fattening pig farms	Most productivity	Medium productive	Least productive	
Share in sample farms (%)	19	60	21	100
Productivity level (EUR per farm): A. historical	972 406	484 711	291 073	538 466
B. if most productive technology adopted	972 406	566 951	381 715	606 525
Change in productivity B/A (%)	0.0	17.0	31.1	12.6
Irish cattle rearing farms	Most productive	Medium productive	Least productive	
Share in sample farms (%)	27	9	64	100
Productivity level (EUR per farm): A. historical	51 103	38 789	30 897	37 018
B. if most productive technology adopted	51 103	54 650	40 123	44 391
Change in productivity B/A (%)	0.0	40.9	29.9	19.9
Irish “cattle other” farms	Medium productive	Least productive	Most productive	
Share in sample farms (%)	52	27	22	100
Productivity level (EUR per farm): A. historical	52 016	23 887	126 235	60 741
B. if most productive technology adopted	78 065	56 789	126 235	82 928
Change in productivity B/A (%)	50.1	137.7	0.0	36.5
Irish sheep farms	Most productive	Least productive	Medium productive	
Share in sample farms (%)	25	38	38	100
Productivity level (EUR per farm): A. historical	79 913	36 392	40 175	48 801
B. if most productive technology adopted	79 913	52 172	58 151	61 542
Change in productivity B/A (%)	0.0	43.4	44.7	26.1

Norwegian cattle farms	Least productive	Most productive		
Share in sample farms (%)	81	19		100
Productivity level (EUR per farm): A. historical	30 823	34 887		31 599
B. if most productive technology adopted	18 823	34 887		21 891
Change in productivity B/A (%)	-38.9	0.0		-30.7
UK crop-livestock farms	Most productive	Least productive	Medium productive	
Share in sample farms (%)	28	29	43	100
Productivity level (EUR per farm): A. historical	374 277	108 261	172 093	210 672
B. if most productive technology adopted	374 277	199 776	211 875	254 302
Change in productivity B/A (%)	0.0	84.5	23.1	20.7
UK pig farms	Most productive	Medium productive	Least productive	
Share in sample farms (%)	28	65	7	100
Productivity level (EUR per farm): A. historical	361 520	265 545	80 924	279 967
B. if most productive technology adopted	361 520	263 591	122 560	281 573
Change in productivity B/A (%)	0.0	-0.7	51.4	0.6
UK poultry farms	Most productive	Least productive	Medium productive	
Share in sample farms (%)	21	4	75	100
Productivity level (EUR per farm): A. historical	270 411	51 282	173 894	189 258
B. if most productive technology adopted	270 411	83 379	173 799	190 470
Change in productivity B/A (%)	0.0	62.6	-0.1	0.6

Note: Assuming the technology of the most productive farm Class 1s also the best for other farm classes.
Source: Tables in document [TAD/CA/APM/WP(2020)2/PART2/FINAL].